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An Investigation of Factors that Influence Passengers' Intentions to Use Biometric Technologies at Airports

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Abstract

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Biometric technologies use the characteristics and measurements from humans to establish or verify their identity. Within an airport setting, biometric technologies can be used to hasten passenger processes such as airport check-in, baggage drop-off or pick-up, and aircraft boarding, thus enhancing the overall passenger experience.

This research investigated the factors that influence passengers' intentions to choose the use of biometrics over other methods of identification. The current study utilized a quantitative research method via an online survey of 689 persons from Amazon ® Mechanical Turk ® (MTurk) and employed structural equation modeling (SEM) techniques for data analysis. The study utilized the theory of planned behavior (TPB) as the grounded theory, while perceived usefulness and perceived ease of use were included as additional factors that could influence individuals' intentions to use new technology.

The study further assessed the impact of passengers' privacy concerns on the intentions to use biometrics and investigated how the privacy concerns moderate the influencing factors of passengers' behavioral intentions. Because of the coronavirus (COVID-19) pandemic that became prevalent at the time of the study, a COVID-19

variable was introduced as a control variable to examine if there were any effects of COVID-19 on passengers' behavioral intentions while controlling for the other variables.

Results showed that for the TPB factors, attitudes and subjective norms significantly influenced passengers’ behavioral intentions to use biometrics, while the effect of perceived behavioral control (PBC) on passengers’ intentions was not significant. The additional factors of perceived usefulness and perceived ease of use did not significantly influence passengers’ intentions. In addition, the hypothesized relationships between privacy concerns and four factors, behavioral intentions, attitudes, PBC, and perceived ease of use were supported, while the relationships between privacy concerns and perceived usefulness and between privacy concerns and subjective norms were not supported.

The examination of the moderating effects found that privacy concerns moderated the relationships between passengers’ intentions and three factors: attitudes, subjective norms, and perceived usefulness. However, because the interaction plots showed that the moderating effects were weak, the effects were not considered to be of much value and were therefore not added to the final model. Results also showed that the control variable (COVID-19) did not significantly influence passengers’ behavioral intentions and passengers’ privacy concerns while controlling for the other variables.

Practically, the study contributed a research model and specified factors that were postulated to influence passengers’ behavioral intentions to use biometrics at airports. Further research would be required to determine additional factors that influence behavioral intentions. Finally, although the moderating effects were not used in the final model, the findings suggest that stakeholders can customize biometric systems and solutions appropriately to cater to passengers' concerns.

Dedication

This dissertation is dedicated to the loving memory of my late parents, Al-Ghali O. Kasim and Kareema A. Kasim, and to the memory of late Lateefah A. Kasim.

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Chapter I: Introduction

This chapter introduces the study of passengers' intentions to use biometrics at airports. First, the background of the study discusses the main uses of biometrics with a specific emphasis on some airports in the United States where the technology has been used. Next, the statement of the problem presents a summary of the topical issues regarding the research on passengers' concerns with the use of biometric systems and clarifies the main areas of focus for the study. The statement of the problem is followed by the purpose statement, which summarizes the general approach adopted in the completion of the study, and the significance of the study, which shows the expected benefits from the results of the study. The chapter then provides the research questions and the hypotheses statements, while the delimitations, limitations, and assumptions that underpin the study are presented. The final sections in the chapter present the definitions of the main terms and a list of acronyms used in the completion of the study.

Background of the Study

Biometric technologies have been used in many industries and for different purposes, such as to improve security and convenience and to deliver enhanced services to individuals and organizations (Nanavati, Thieme, & Nanavati, 2002). Because biometrics involves the use of personal physiological or behavioral characteristics, the technology can help ensure a high degree of certainty about an individual's identity and help to reduce risks of financial losses for individuals and organizations (Nanavati et al., 2002). Regarding biometrics use in the air transport industry, a study by the air travel intelligence company, OAG, revealed that the most likely uses of biometrics at airports include security access, check-in, boarding, accessing itineraries, and for customs and immigration purposes (OAG, 2018).

Passenger forecast data published by both the International Civil Aviation Organization (ICAO) and the International Air Transport Association (IATA) suggest that the number of air transport passengers worldwide should double from the reported figure of 4.1 billion passengers in 2017 to approximately 8.2 billion passengers a year by 2037 (IATA, 2018; ICAO, 2018). Biometric technology will likely play a key role in helping to manage passenger growth, improve the overall passenger experience, and strengthen the overall security of air travel. For example, in the United States (U.S.), the Department of Homeland Security (DHS) has chosen facial recognition technology to manage biometric entry and exit procedures for air, land, and sea passengers into the U.S. To operationalize this in air transport, the Customs and Border Protection (CBP) has worked in conjunction with some airlines and airports to progressively change the passenger identification and verification process from a physical document-based procedure to one that is based primarily on a biometric transaction (U.S. DHS, 2018).

A list of the airports in the U.S. that have deployed the CBP Traveler Verification Service (TVS) to support immigration entry and exit is shown in Table 1.

Table 1

Airports with Traveler Verification Service (TVS) Use

Airport	Traveler Verification Service (TVS) use
Hartsfield–Jackson Atlanta International Airport (ATL)	Entry/Exit
Boston Logan International Airport (BOS)	Exit
Ronald Reagan Washington National Airport (DCA)	Exit
Dallas/Fort Worth International Airport (DFW)	Exit
Detroit Metropolitan Wayne County Airport (DTW)	Exit
Newark Liberty International Airport, New Jersey (EWR)	Exit
Fort Lauderdale-Hollywood International Airport (FLL)	Entry/Exit
William P. Hobby Airport, Houston (HOU)	Exit
Dulles International Airport, Washington (IAD)	Entry/Exit
George Bush Intercontinental Airport, Houston (IAH)	Entry
John F. Kennedy International Airport, New York (JFK)	Entry/Exit
McCarran International Airport, Las Vegas (LAS)	Entry/Exit
Los Angeles International Airport (LAX)	Entry/Exit
Orlando International Airport (MCO)	Entry/Exit
Miami International Airport (MIA)	Entry/Exit
Minneapolis–Saint Paul International Airport (MSP)	Exit
Chicago O'Hare International Airport (ORD)	Exit
San Diego International Airport (SAN)	Entry/Exit
Seattle-Tacoma International Airport (SEA)	Exit
San Jose International Airport (SJC)	Entry/Exit
Salt Lake City International Airport (SLC)	Exit
Tampa International Airport (TPA)	Exit

Note. Compiled by Author using data from U.S. DHS (2019).

In addition to the use for immigration purposes where passengers may not have a choice, airports and airlines also use biometric technology in other areas to facilitate a seamless travel experience for passengers. Most notably, Delta has inaugurated a terminal at Atlanta Airport (ATL) with an optional biometric end-to-end service using facial recognition technology for the entire passenger experience, including check-in, baggage check and drop-off, security check, and aircraft boarding (CNN, 2018). In other examples, JetBlue has a fully-integrated biometric self-boarding gate at John F. Kennedy Airport, New York (JFK), while American Airlines announced that the trial earlier completed at Los Angeles International Airport (LAX) would be evaluated with a view to expanding the use of biometric boarding to other locations within the airline's network (Genter, 2019). A list of airlines and the airports in the U.S. where biometric boarding has either been used in the past or is currently in use is shown in Table 2.

Table 2

Airlines with Biometric Boarding and Corresponding Airports

Airline	Airports
American Airlines	Los Angeles (LAX), Dallas/Fort Worth (DFW)
British Airways	Los Angeles (LAX)
Delta	Atlanta (ATL), Ronald Reagan Washington (DCA), Detroit Metropolitan (DTW), New York (JFK), Minneapolis–Saint Paul (MSP)
Jet Blue	Boston Logan (BOS), Ronald Reagan Washington (DCA), Fort Lauderdale-Hollywood (FLL), New York (JFK)
Lufthansa	Los Angeles (LAX)

Note. Compiled by Author.

Apart from the mandatory uses that may be specified by national or government agencies, the deployment of biometric technologies normally includes the statement that the use of the system is optional. Passengers will then be able to make the decision to complete the identification or verification process through the traditional way using passports and paper boarding passes. Although there has been some research in general about passengers' concerns with the use of biometrics, an area that appears to be less studied is in identifying the factors that affect passengers' intentions to choose or not to choose to use biometrics. This research targeted and reduced the gap in the literature on passengers' intentions to use biometrics.

The current study also considered the different viewpoints over the impact of biometrics on passengers' human rights and attitudes, specifically regarding their privacy concerns. For example, Morosan (2016) found that privacy concerns were not significant in passengers' intentions to utilize biometric e-gates. Merlano (2016) also noted that privacy concerns did not feature amongst the complaints from passengers, while Farrell (2016) suggested that the use of facial recognition as a form of biometric technology in airports can be considered less sensitive from a passenger privacy perspective. In another study, Morosan (2018) found that the general concerns of air travelers' regarding their willingness to provide biometric information were offset by the benefits, including the perceived additional security provided using biometrics. Additionally, the studies by Neo, Rasiah, Tong, and Teo (2014, 2016) noted that the use of biometric technology by passengers posed a risk of privacy invasion.

Statement of the Problem

Based on the notion that the usage of biometrics systems should provide positive experiences for passengers, it was anticipated that up to 63% of airports and 43% of airlines globally will invest in biometric technologies over the three-year period from 2018 to 2020 (SITA, 2018). However, Miltgen, Popovič, and Oliveira (2013) highlighted a possible concern that an inadequate examination of public concerns could lead to failures in the implementation of biometric systems. Furthermore, it is important that the planned investments in biometrics by airports and airlines should also be supported with reliable research regarding the intended use by passengers.

The study by the Consumer Technology Association (CTA) focused on consumers' perception levels with the different uses of biometrics and the trust in organizations responsible for managing biometric information. The study reported that 62% of U.S. adults that had used biometrics were comfortable with its use at airports or national borders (CTA, 2016). More recently, the information technology company UNISYS, in its annual security index survey, reported on U.S. air traveler's comfort with biometric identification. The results from the survey showed that 81% of U.S. air travelers approve of the use of biometrics to enhance security, reliability, and convenience at airports (UNISYS, 2019).

While these studies recognize the use of biometric technologies to ease the burdens of passengers at airports, few studies have considered the relationship between the availability of the technologies and the intentions of passengers' regarding the use of the technologies. Furthermore, it appears that the literature lacks sufficient empirical research used to investigate any additional factors that could influence passengers' behavioral intentions to utilize these technologies and to determine the effect of passengers' privacy concerns on these factors. Further study is therefore required to identify the factors that affect the voluntary actions of passengers' regarding their intentions to make use of biometric systems at airports.

Purpose Statement

The purpose of the current study was to utilize a quantitative research method and correlational design to investigate factors influencing passengers' behavioral intentions to use biometric technologies at airports. The research employed the theory of planned behavior (TPB) as grounded theory, while perceived usefulness and perceived ease of use were included as additional influencing factors. The study featured a survey of 689 persons from the Amazon ® Mechanical Turk ® (MTurk) platform, while the data collected was evaluated using structural equation modeling (SEM) techniques to develop and test a theoretical model that identified the factors of influence. Since there has been limited empirical research dedicated to studying privacy with passengers' use of biometric technologies at airports, this study also explored the moderating effects of passengers' privacy concerns on the factors that influence passengers' behavioral intentions.

Significance of the Study

As air travel expands worldwide, the requirement to identify and process passengers efficiently at airports means that the use of biometrics is likely to contribute to passengers' perceptions of their overall travel experiences (Morosan, 2012a, 2012b, 2016). The findings from this research are beneficial to all the major practitioners in the aviation industry – including government or regulatory agencies, airports, airlines, service providers, and passengers. While passengers may not be able to decline the use of biometrics in cases where it is mandated by the government, this study is important as it investigated the role of privacy in determining passengers' behavioral intentions. The government can also benefit from increased security and access to reliable data collected from biometrics enrollment.

For the airports and airlines, the expected investments in biometric technologies support the need for further research in the technology. The increased use of biometrics will likely lead to improved passenger processing times and an overall improvement in passengers' travel experience. Crew identification and employees' access to sensitive locations at the airport are also some of the other areas that could feature increased use of biometrics.

This study also contributed to the debate on passengers' behavioral intentions by creating a model of factors that influence passengers' intentions to use biometric technologies at airports. The research model was developed using factors of the TPB and perceived usefulness and perceived ease of use as additional factors. A further benefit of the current study was the assessment of the moderating effects of privacy on the TPB components and the additional factors.

Research Questions

The current study examined these four research questions:

- What are the factors that influence passengers' behavioral intentions to use biometric technologies at airports?
- How do these factors influence passengers' behavioral intentions to use biometric technologies at airports?
- What is the effect of privacy on passengers' behavioral intentions to use biometric technologies at airports?
- How do privacy concerns moderate the factors that influence passengers' behavioral intentions to use biometric technologies at airports?

Hypotheses

This study investigated the following hypotheses statements:

H_1: Attitudes positively influence passengers' intentions to use biometric technologies at airports.

H_{1-1}: The level of privacy concerns will moderate the positive relationship between passengers' attitudes and intentions to use biometric technologies at airports.

H_2: Subjective norms positively influence passengers' intentions to use biometric technologies at airports.

H_{2-1}: The level of privacy concerns will moderate the positive relationship between subjective norms and intentions to use biometric technologies at airports.

H_3: Perceived behavioral control positively influences passengers' intentions to use biometric technologies at airports.

H_{3-1}: The level of privacy concerns will moderate the positive relationship between perceived behavioral control and intentions to use biometric technologies at airports.

H_4: Perceived ease of use positively influences passengers' intentions to use biometric technologies at airports.

H_{4-1}: The level of privacy concerns will moderate the positive relationship between perceived ease of use and intentions to use biometric technologies at airports.

H_5: Perceived usefulness positively influences passengers' intentions to use biometric technologies at airports.

H_{5-1}: The level of privacy concerns will moderate the positive relationship between perceived usefulness and intentions to use biometric technologies at airports.

H_6: Privacy concerns negatively influence passengers' intentions to use biometric technologies at airports.

H_7: Attitudes negatively influence passengers' privacy concerns toward biometric technologies at airports.

H_8: Perceived ease of use negatively influences passengers' privacy concerns with the use of biometric technologies at airports.

H_9: Perceived usefulness negatively influences passengers' privacy concerns with the use of biometric technologies at airports.

H_{10}: Subjective norms are related to privacy concerns with the use of biometric technologies at airports.

H_{11}: Perceived behavioral control is related to privacy concerns with the use of biometric technologies at airports.

Delimitations

There are several delimitations that defined the boundaries of this study. One delimitation of the study is the choice to focus the research on only factors that influence passengers' behavioral intentions to use biometric technologies at airports. The study did not cover the mandatory uses of biometrics or the use of biometrics for other purposes; neither did it cover the use of other technologies that may be available to passengers at any point during air travel. The study was also delimited to the adoption of the TPB as theoretical framework, quantitative research method, correlational design, and the use of SEM as the data analysis method.

The present study was also delimited to focus on U.S. airports only since an attempt to generalize outside the U.S. will require time and resources that are beyond the scope of this study. With the Federal Aviation Administration (FAA) data showing one billion passengers in the U.S. in the 2018 financial year (FAA, 2019), the target population is considered enough to provide practical information to all stakeholders. Furthermore, the study could easily be replicated to other regions or areas.

Participants selected for the study were delimited to a convenience sample from MTurk. The use of MTurk has been supported by studies that show that it allows researchers to obtain data that is reliable, from a large and diversified pool of persons, and at costs lower than traditional methods (Johnson & Borden, 2012; Rice, Winter, Doherty, & Milner, 2017). Finally, while there are other types of biometric technologies that could be utilized at airports, this study focused on facial recognition technology as the specific type of biometric technology.

Limitations and Assumptions

Four limitations of the current study are identified. First, the findings of the study may not be generalizable to a wider population outside of those persons who participate in MTurk and complete online human intelligence tasks. Chapter III provides further explanation on the use of a sample from MTurk.

Second, the electronic questionnaire utilized for the survey is a potential limitation as participants could find the range of responses in the questionnaire limited. To mitigate the limitation, the questionnaire included an option for respondents to indicate any additional comments separate from the response categories. Third, the adoption of a cross-sectional time horizon was also a potential limitation as the responses from participants may be affected by conditions that could be occurring at the specific time. The effect of the limitation can be minimized through future research and repeating the survey at different times.

Fourth, self-administration of the survey through the Internet, as utilized in the study, could create a potential limitation that the questions on the survey may not be interpreted the same way by different respondents (Vogt, Gardner, & Haeffele, 2012).

The effect of the limitation was minimized by confirming that the questions were clear and unambiguous and by using a pilot study to test the questionnaire before it was deployed for the main study.

The present study was based on some assumptions. It was assumed that participants' declaration of intention to use biometrics will be followed by the actual use of biometrics. The assumption is supported by the review of the available literature on the TPB, which showed that actual behaviors could be predicted from the intentions to engage in the behavior (Ajzen, 1985, 2005; Madden, Ellen & Ajzen, 1992). Furthermore, it was also assumed that an individual passenger would be solely responsible for the decision to make use of biometrics in an airport setting.

While the study was delimited to a convenience sample of participants from MTurk, it was assumed that the participants that choose to respond represent the target population. The review of studies that utilized MTurk samples provided justification to support this assumption (Berinsky, Huber, & Lenz, 2012; Paolacci, Chandler, & Ipeirotis, 2010).

Finally, it was assumed that participants completed the questionnaire truthfully. It is sensible to assume that participants' responses reflected their honest opinions since the participants were reassured of the measures utilized by the researcher to protect their anonymity. Participants were also reminded that the choice to participate in the study was voluntary. Furthermore, they could decide to discontinue at any time during the survey with no consequences.

Summary

This chapter presented an introduction to the study of passengers' intentions to use biometrics. The background of the study provided the main uses of biometrics with a specific focus on some airports and airlines. The problem statement considered the current state of the research on passengers' concerns with the use of biometric systems and highlighted the gap from studies of biometrics that the study intended to fill. The chapter also presented a purpose statement which summarized the reason for the study and the method chosen to accomplish the aims of the research.

The remainder of the chapter presented the significance of the study, the research questions, and the hypotheses statements, while the delimitations that defined the boundary for the study are stated. Finally, the limitations of the study and assumptions that underpin the study are presented along with a definition of the main terms and a list of acronyms that were used in the study.

Definitions of Terms

Attitude	A learned predisposition to respond in a consistently favorable or unfavorable manner with respect to a given object (Fishbein & Ajzen, 1975).
Behavior	An observable act of a subject that can be studied in its own right (Fishbein & Ajzen, 1975).
Behavioral Intention	A person's subjective probability that he or she will perform the behavior in question (Fishbein & Ajzen, 1975).

Biometrics	The automated use of physiological or behavioral characteristics to determine or verify identity (Nanavati et al., 2002).
Informational Privacy	The unauthorized collection, storage, and usage of biometric information (Nanavati et al., 2002).
Perceived Behavioral Control (PBC)	The perceived ease or difficulty of performing a behavior (Ajzen, 1991).
Perceived Ease of Use (PEOU)	The degree to which a user believes that using a system would be free of effort (Davis, 1989).
Perceived Self-Efficacy	The belief in one's ability to succeed in a specific task or to exercise control over events that affect oneself (Bandura, 1977).
Perceived Usefulness	The degree to which a user believes that using a system would enhance the performance of a job or task (Davis, 1989).
Personal Privacy	An inherent discomfort an individual may feel when encountering biometric technology (Nanavati et al., 2002).
Subjective Norms	The perceptions of an individual that most people that are important to the individual think the individual should or should not perform the behavior in question (Fishbein & Ajzen, 1975).

List of Acronyms

AGFI	Adjusted Goodness of fit Index
AMOS	Analysis of Moment Structures
AVE	Average Variance Extracted
CBP	Customs and Border Protection
CFA	Confirmatory Factor Analysis
CFI	Comparative fit Index
CNN	Cable News Network
CR	Construct Reliability
CTA	Consumer Technology Association
DHS	Department of Homeland Security
DIT	Diffusion of Innovations Theory
ERAU	Embry-Riddle Aeronautical University
FAA	Federal Aviation Administration
GFI	Goodness of fit Index
GOF	Goodness-of-fit (GOF) indices
HIT	Human Intelligence Task
IATA	International Air Transport Association
ICAO	International Civil Aviation Organization
IM	Instant Messaging
IRB	Institutional Review Board
MLE	Maximum Likelihood Estimation
MP	Mobile payment

MTurk	Amazon ® Mechanical Turk ®
NFC	Near-field Communication NFC
NFI	Normed Fit Index
OAG	Official Airline Guide
OCM	Online Crowdsourcing Market
PIA	Privacy Impact Assessment
RMSEA	Root Mean Square Error of Approximation
SEM	Structural Equation Modeling
SITA	Société Internationale de Télécommunications Aéronautiques
SPSS	Statistical Package for the Social Sciences
TAM	Technology Acceptance Model
TPB	Theory of Planned Behavior
TRA	Theory of Reasoned Action
TSR	Theory of Self-Regulation
TVS	Traveler Verification Service
UNISYS	United, Information and Systems
URL	Uniform Resource Locator

Chapter II: Review of the Relevant Literature

This chapter presents a review of some of the available literature related to the study. First, it presents a summary of the strategy and the main keywords used for the literature search. Next, it presents an overview of basic biometric principles and an outline of the gaps identified in the literature. The chapter then presents a discussion on the relevant central ground theory selected for the study and examines the key variables influencing passengers' intentions that were included as factors in the model. The chapter also presents a review of previous studies of passengers' use of biometrics at airports and ends with a presentation of the theoretical framework and hypotheses used for the study.

Strategy and Keywords

The literature review was conducted using printed material and resources retrieved online via the Embry Riddle Aeronautical University (ERAU) Hunt Library. In addition to the Eaglesearch® function of the library, the Research Databases that were used include ProQuest Central® and ScienceDirect®. Google Scholar® was used to search for scholarly literature in the areas of passengers' intentions and biometrics at airports. Keywords used for the searches include *theory of planned behavior, biometric technology, biometrics, airports, biometrics at airports, biometrics and privacy concerns, biometrics and security, passengers' intentions, biometrics standards, and technology acceptance.*

Overview of Biometric Technologies

A general explanation of biometric technologies is provided as a basis for understanding the principles of biometrics use described within this research study. The term biometrics originates from two Greek words *bio*, which means life, and *metric*, which means to measure (Di Nardo, 2009). Biometrics therefore refers to the use of characteristics and measurements from individuals to establish or verify their identity. The basic premise of biometrics relates to the use of computers and machines to provide identification based on unique physiological and behavioral characteristics (Adeoye, 2010; Langenderfer & Linnhoff, 2005). The accuracy of biometrics has been well demonstrated to the extent that is has been referred to as a 'body password' (Adeoye, 2010). While the more common biometric systems in use for identification and recognition include images and scans of fingerprints, signatures, hands, faces, and irises of the eyes, humans can also be recognized by their gait, retina, veins, body odor, and ear pattern. Moradoff (2010) identified three categories in the use of biometrics-anatomical, physiological/biological, and behavioral. He suggested that to give improved results, biometric technologies should comprise of elements of both behavioral and anatomical or physiological measurements.

The basic principle in how biometrics works is reflected in three essential steps: enrollment, template, and matching (Adeoye, 2010; Moradoff, 2010). Enrollment refers to the process of collecting biometric samples or characteristics from individuals. After enrollment, the record of the enrollee's biometrics is stored as a template. Finally, the matching process involves the comparison of a submitted biometric sample with the biometric records in a database for authentication. Authentication could either be for comparison against one (verification) or many (identification). Verification involves checking whether the person is who they say they are, while identification involves checking who the person is. Langenderfer and Linnhoff (2005) noted that in general, verification systems are more accurate than identification systems.

Nanavati et al. (2002) identified three main roles that an individual can assume in the interactions with biometric systems. These are citizen, employee, and customer (consumer). With citizen-facing applications, authentication of an individual is performed by a government agency for law enforcement purposes, while employee-facing applications are focused on authentication of an individual in interactions with their employer. Customer-facing authentication is concerned with the authentication of an individual as a condition for a transaction involving a product or a service provided by a seller to a consumer. Additional characteristics regarding the roles of individuals in the interactions with biometric systems is presented in Table 3. The emphasis of the present study was on the use of biometrics in a customer-facing scenario.

Table 3

Roles of Individuals in the Use of Biometric Systems

Characteristic	Citizen-facing	Employee-facing	Customer-facing
Mode of use	Likely to be mandatory for all users	Likely to be mandatory for the specific users	Optional for users of a provider's customer base
Data storage and control	Centralized storage by a government entity	May or may not be centralized, control by a private or public organization	Storage and control by the provider of the service
Mode of authentication	Possibly based on identification	Possibly based on verification	Possibly based on verification
Scale of deployment	Large-scale deployments at State or Federal levels	Deployment is as large as the organization	Based on the provider's customer base
Privacy Risk	Greater privacy risks, requires adequate controls	Privacy implications are less severe	Less likely to pose privacy risks if adequate controls are provided

Note. Compiled by Author. Adapted from "Biometrics: Identity verification in a networked world, "by S. Nanavati, M. Thieme, and R. Nanavati, 2002.

The literature on biometrics and the descriptions provided in this section suggest that there are interactions between biometrics and behaviors. It is expected that the study of passengers' intentions and behaviors in this research further strengthened the contributions made by this study to the literature on passengers' intentions. The next section highlights some of the research gaps that motivated this study.

Gaps in the Literature

There has been some prior research into the acceptance of biometric technologies. For example, Emami, Brown, and Smith (2016) found that the continuous installation and deployment of such technologies depends on users' willingness to adopt the technology. However, the sample in their study (*n* = 446) was limited to Australians who were victims of identity crime in the past on their perceptions regarding their future use of biometrics. The results showed that 68% of respondents would consent to the use of some form of biometrics in the future. The study by Emami et al. (2016) also confirmed that public acceptance of biometric technology use was high where the context involved airport security, but passengers were less enthusiastic about the use of biometrics for marketing purposes. One recommendation from their study suggested the continuous monitoring of users' attitudes to determine the willingness to make use of biometrics in the future (Emami et al., 2016).

Similarly, Morosan (2012a) explored the attitudes of travelers and their intentions to use registered traveler biometric systems (RTBS) at airports. The RTBS are voluntary biometric applications that travelers can choose to use at any time at airports and allow regular travelers access to dedicated and faster processing (Lazarick & Cambier, 2008).

In his study, Morosan (2012a) used a variant of the technology acceptance model (TAM) and collected data from the southwest of the United States with a sample (n = 168). He found that travelers' attitudes toward RTBS were the most significant factor in their intentions to use the systems. Furthermore, he also found that their perceptions of privacy and usefulness had significant effects on their attitudes, while ease of use had only a minor effect. Although his study provided valuable findings regarding attitudes and intentions of travelers, his choice of sample appeared to be slightly biased. It is also suggested that the use of the TAM created a limitation of task setting common to TAM-based studies since there is a limitation of TAM when the model is not within the task environment (Venkatesh, Morris, Davis, & Davis, 2003).

In concluding the study, Morosan (2012a) suggested that biometric systems could be applied to solve travel security problems and proposed areas for further research including immigration, entry, access, and payment systems. Since the theory of planned behavior (TPB) is related to the intention of a person to perform a specified behavior, the use of the TPB in this study provided for a greater evaluation of the intentions of passengers to use biometrics and helped to expand the current literature on the use of biometrics.

The increased use of biometric technologies has also created a need for additional research to ensure that the factors that could predict the voluntary use of biometric systems at airports are adequately understood. For example, the response of travelers to a possible threat to their privacy from the use of biometrics at airports appears not to have been thoroughly examined from the available literature. The current study also added to the literature on passengers' intentions by studying how passengers' privacy concerns moderate the influencing factors of passengers' behavioral intentions. Additionally, perceived usefulness and perceived ease of use were studied as additional factors that could affect passengers' intentions to use biometric technology. The research gaps identified in this section thus justified this study. The next section reviews the theoretical foundation that underpinned this current study.

Theoretical Foundation for the Study

The theoretical foundation provides a perspective that specifies the relationships (in terms of extent and direction) among the variables in the study (Creswell, 2014). A strong theoretical base is, therefore, essential to ensure the study is well grounded. The theoretical foundation selected should also help to provide a good understanding of the reasons behind passengers' behaviors. Thus, the literature was examined to determine the foundational theories that could be applicable to this study.

Foundational Theories Considered. While there are several theories that could be applicable, two theories that were considered as theoretical foundation for this study are reviewed in this section.

The Diffusion of Innovations Theory. The diffusion of innovations theory (DIT), as stated by Rogers (1983) was one of the theories considered for the study. The DIT seeks to explain how a technological innovation is transmitted gradually through defined channels and within a specific social system. To break down the four elements of the DIT further, whereas an innovation is considered a recent practice or idea within that social system, the transmission is the passing of messages from one individual to another. The time dimension is an important aspect of every activity in the innovations process, while a social system includes individuals, groups, or organizations that come together to achieve a common goal. Thus, the DIT considers the spread, how the innovation is adopted or rejected, and the subsequent change in the social system (Rogers, 1983).

The rate of adoption is described as the level of acceptance of an innovation by persons belonging to a group over a given time period. Rogers (1983) theorized that innovations are diffused gradually over a long period and in a manner resembling an S-shaped curve. The typical growth period of an innovation starts slowly, gradually attains rapid growth, following which the rate of adoption maintains a steady growth and eventually decreases. Depending on the level of innovativeness, five classes of the members of a social system are identified: innovators, early adopters, early majority, late majority, and laggards (Rogers, 1983; Surry & Farquhar, 1997). The concept also introduced five attributes of an innovation, namely: relative advantage, compatibility, complexity, trialability, and observability, as being important features that could help clarify the different rates of adoption.

Previous studies have utilized the DIT to study the adoption of innovations in various sectors. In one study, Al-Jabri and Sohail (2012) used the DIT to study the adoption of mobile banking technology. Findings from their study showed that three attributes - relative advantage, compatibility, and observability had positive impacts on adoption, while trialability and complexity did not have significant effects on adoption. However, even though the results from their study had practical implications for the use of mobile banking technology in a new environment, they acknowledged that the use of additional variables should help to understand actual use and predict usage intentions of the technology more accurately (Al-Jabri & Sohail, 2012).

In the area of security, Iles et al. (2017) investigated the adoption of a type of security technology – portable radiation detectors. These are small radiation detection devices that can be carried by individuals on their person. Their study was significant as they integrated the DIT with the theory of reasoned action (TRA) and the health belief model. Results from their survey (n = 1,482) found support for the factors of the DIT and noted that the adoption of the technology can be enhanced using effective communication and non-financial initiatives such as recognitions and the idea of a greater good (Iles et al., 2017). One of their recommendations was to suggest the use of the TPB with its perceived behavioral control variable as a basis for predictive modeling.

Lee, Hsieh, and Hsu (2011) blended the DIT with the technology acceptance model (TAM) and focused on the behavioral intentions of employees to use an e-learning system. Their study (n = 552) confirmed that the five attributes of an innovation significantly affected employees' behavioral intentions to make use of e-learning systems. Overall, while the integration of the DIT and the TAM was considered successful, they suggested that an extended model of TAM can be used to investigate users' technology acceptance and predict behavioral intentions (Lee et al., 2011).

On their part, Liu and Li (2010) used the DIT to examine mobile Internet diffusion among the adopter groups of the social system. The findings from their study revealed notable differences in users' perceptions during the different innovation adoption and diffusion stages. They recommended that the differences in adopter groups should be considered in efforts to promote adoption of the technology (Liu & Li, 2010).

In summary, while it was found that the DIT can give good insights into the diffusion process of an innovation (Liu & Li, 2010), other authors have also identified some notable limitations of the theory. For example, it was reported that the DIT does not show the link between the attitudes of users and their acceptance or rejection of an innovation (Chen, Gillenson, & Sherrell, 2002; Karahanna, Straub, & Chervany, 1999). Also, there is not enough clarity on the relationship between the innovation-acceptance/rejection process and the features of the innovation (Kiwanuka, 2015). With the DIT, it appears that there is a lot of focus on the innovation and not enough attention to an individual's decision regarding acceptance or rejection of the innovation.

Another limitation of the DIT relates to the innovation-decision process that usually occurs in a sequence as part of the diffusion process. According to the DIT, the stages by which an innovation diffuses through a system are: awareness of the need for an innovation (knowledge and persuasion), adoption or rejection of the innovation (decision), initial use of the innovation to test it (implementation), and continued use of the innovation, that is, confirmation (LaMorte, 2018b; Rogers, 1983). However, as noted by Lyytinen and Damsgaard (2001), diffusion of complex technologies does not occur in a sequential or linear pattern. For example, a decision may precede the knowledge and persuasion stage. It is therefore difficult to fully understand the differences between the choices of the individuals in the adopter groups without the use of additional constructs. Therefore, the DIT was not an appropriate theory for this study since there was a need to examine the attitudes and behaviors of individuals regarding the decision to use biometrics.

Theory of Reasoned Action. Another theory that was considered for the present study is the theory of reasoned action (TRA), as stated by Fishbein and Ajzen (1975). The TRA is focused on the role of behavioral intention as it relates to the attitudes-behaviors relationship. Per the conceptual framework of the theory, a person's behavioral intention depends on two factors: the attitude toward the behavior and the subjective norms relating to that behavior.

The use of the TRA in various studies to predict human intentions and behaviors has been well documented in the literature. This section will review three such studies that used the TRA to examine user intentions in the field of information technology. The study by Davis, Bagozzi, and Warshaw (1989) investigated the potential of the TRA to predict and explain how users accept or reject computer-based technology. Their study also incorporated the TAM, which is considered an extension of the TRA that focuses particularly on computer usage behavior. Although the results from their study showed that a person's computer use could be determined from their intentions, it was noted that the attitudes construct in their study was unable to fully explain the causal linkages between beliefs and intentions. They called for further research to establish the conditions under which attitudes can mediate the link between belief and intention (Davis et al., 1989).

A study by Van Slyke, Ilie, Lou, and Stafford (2007) used the TRA to understand the factors influencing individuals' intentions to use instant messaging (IM) systems. Their study synthesized the TRA (as a theoretical framework focusing on decisions to use technology) and the DIT (to provide a set of constructs known to impact attitudes and intentions). They found that individuals' intentions to use the IM system were influenced by their attitudes and their perceptions of the number of people using the system (Van Slyke et al., 2007). The results also confirmed findings from previous studies (Karahanna et al., 1999) that attitudes were significant to individuals' intentions to continue with the use of the system while subjective norms were not (Van Slyke et al., 2007).

A similar study by Peslak, Ceccucci, and Sendall (2010) surveyed students (*n* = 128) at a small southeast U.S. university. It was thought that the use of students was appropriate as they were most active in using the technology (Peslak et al., 2010). Their findings were similar in that attitude had a direct influence on behavior. Furthermore, while subjective norms were positively associated with intentions, there was no direct influence on behavior. They suggested that further study would be required to confirm the findings that behavior can be improved through attention to the significant influencing factors of attitude, subjective norms, and intention (Peslak et al., 2010).

Two of the three studies reviewed used additional theories with the TRA to provide a comprehensive framework to help explain user attitudes and intentions. Despite the overall utility of the TRA in studies of behavior prediction (Ryan & Bonfield, 1980; Sheppard, Hartwick, & Warshaw, 1988), it was noted that the TRA assumes that the behaviors are within an individual's full volitional control. This control implies that the person can decide on his or her own whether to perform the behavior. The TRA is therefore considered to have a limitation in addressing behaviors when individuals lack complete volitional control (Ajzen, 1985).

Foundational Theory Selected. The theory utilized for the current study is the theory of planned behavior (TPB), as stated by Ajzen (1985, 1991). The TPB was selected as the theoretical foundation due to its ability to predict an individual's intentions toward the performance of a given behavior. The TPB is also deemed appropriate as it has been widely used as a theoretical base in different subject areas.

Casper (2007) reported that the TPB had been used in approximately 600 studies of behavior prediction in the 20-year period prior to his study.

One other reason for the use of the TPB is that the TPB allowed for the expansion of the TRA through the incorporation of perceived behavioral control (PBC) in the model. Various studies also show that the addition of PBC catered to the limitation of partial volitional control by individuals inherent in the TRA, and thus enhanced the prediction of behavioral intention and behavior (Chen, Fan, & Farn, 2007; Madden et al., 1992; Tsai, 2010).

The relationship between the two theories can be further explained in terms of the subjective probability of success and the degree of control over a behavior. The two theories are similar when the probability and control reach their maximum values. This situation is volitional behavior in which the TRA can be directly applied. However, when the probability of success and actual control are not at their maximum, the TPB will be more appropriate (Ajzen, 1985).

Theory of Planned Behavior (TPB)

The central notion of the TPB is related to the intention of an individual to accomplish a given behavior. The theory as postulated by Ajzen (1985, 1991) states that a person's intention to perform a given behavior depends on three factors: attitude, subjective norms, and perceived behavioral control (PBC). Attitude toward the behavior measures a person's assessment of the behavior, subjective norms are the perceived social pressures felt by the individual, while the person's PBC is the perceived ease or difficulty of performing the behavior. PBC may also affect behavior either directly or indirectly, through intentions (Ajzen, 1991).

Origin of the TPB. The origin of the TPB can be traced from studies examining relationships between attitudes and behaviors. The TPB was developed as a modification of the TRA. It is considered an expansion of the TRA that takes care of the TRA's limitations of handling the behaviors of individuals when they lack complete volitional control (Ajzen, 1991). Although the notion that a person's behavioral accomplishment depends on motivation (equivalent to intentions in the TPB) and ability (equivalent to behavioral control in the TPB) is not a new concept, the TPB emphasized the importance of actual behavioral control (Ajzen, 1991).

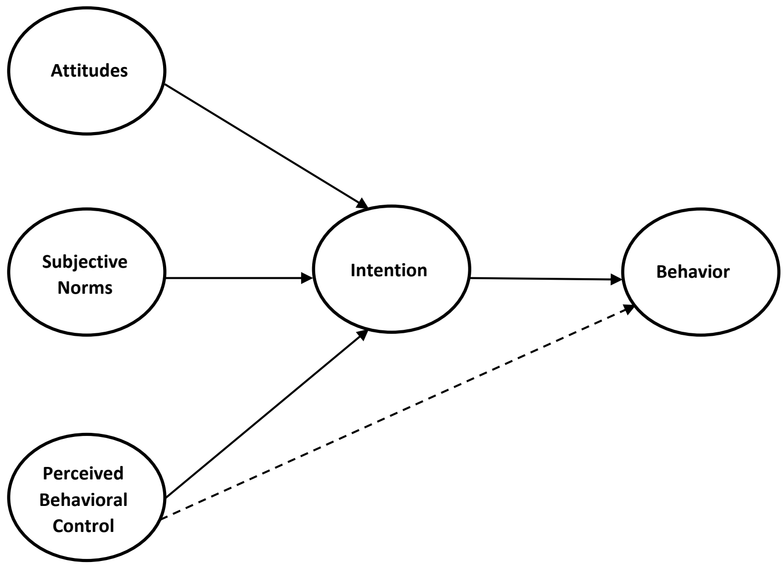
In the theory that was first presented by Ajzen (1985), the TPB considered intentions and the other theoretical constructs in relation to an attempt to perform a given behavior instead of the actual performance. Subsequent research, however, has used measures that deal with the actual performance of behavior as they have shown to be strongly correlated with measures that relate to the attempt to perform a behavior (Ajzen, 1991). There has also been focus on developing theories that could improve the predictive power of attitudes (Armitage & Conner, 2001).

Leone, Perugini, and Ercolani (1999) noted that the TPB developed from a history of models of attitude-behavior relationships. They compared focal variables of three theories, TRA, TPB and the theory of self-regulation (TSR) and concluded that the TRA and TPB were the best known and the most widely applied models for predicting behavior which are based on the attitude construct. Armitage and Conner (2001), on their part, reported that the TRA and TPB were integrated models of behavior that include other factors of behavior, such as intentions or social norms.

Components of the TPB. There are five components in the TPB model. The first three - attitudes, subjective norms, and perceived behavioral control (PBC) are postulated to be conceptually independent factors of the remaining two - intentions and behaviors (Ajzen, 1991, 2005). Attitudes, or attitudes toward the behavior, is the positive or negative assessment of a person's disposition regarding the behavior. Subjective norms are a social factor that considers a presumed peer pressure that influences the performance of the behavior, while PBC is the individual's expectation of the ease or difficulty of performing the behavior (Ajzen, 1991). Fishbein and Ajzen (1975) provided formal definitions of intention as "a person's location on a subjective probability dimension involving a relation between himself and some action" (p. 288) and behavior as "observable acts that are studied in their own right" (p. 13). Figure 1 shows the TPB model with the components and the relationships between them.

Figure 1

TPB Model Showing Components and Relationships



Note. Adapted from "The theory of planned behavior," by I. Ajzen (1991), with permission from Elsevier.

Fishbein and Ajzen (1975) described attitude as the disposition to consistently provide a response (either favorable or unfavorable) to a specific situation. This description also emphasizes an individual's overall positive or negative assessments of performing a behavior. It is thought that an individual's desire to perform a behavior is stronger when there is a more favorable attitude toward the behavior (Armitage & Conner, 2001). To fill some of the conceptual gaps from prior studies, Ajzen (2005) linked attitudes, personality traits, and behaviors. He concluded that attitudes and personality traits were theoretical constructs that are implied from measurable observations and could make individuals be inclined to the specific attitude or trait under consideration.

Subjective norms consider a person's environment and the effects on behavior. Regarding a specific behavior, Fishbein and Ajzen (1975) noted that subjective norms are beliefs by an individual that the most important people to that individual support the behavior. These perceptions are normally built up from normative beliefs (from specific individuals or referents) and from a desire to conform to the wishes of the referents. The subjective norm is viewed as an important determinant of a person's intention to accomplish a specific behavior (Armitage & Conner, 2001; Fishbein & Ajzen, 1975).

The concept of PBC was added to the TRA to cater for circumstances when individuals may not possess the required full volitional control over the specific behavior (Ajzen, 2002). It is closely related to the notion of self-efficacy of Bandura (1977) in that both PBC and self-efficacy are focused on the perceived ability of an individual to perform a behavior (Ajzen, 2002; Bandura, 1977). Per the TPB, the effect of PBC on behavior could either be direct or indirect.

The direct path of PBC to behavior is presumed to indicate an individual's effective control over the performance of the behavior, while an indirect effect could occur through the impact on intention (Ajzen, 2002, 2005). The effect on actual behavior should be significant when it is likely that there are some aspects of the behavior that are not within the individual's volitional control, and when there are accurate perceptions of the control over the actual behavior (Madden et al., 1992).

In addition, the relationship between intention and behavior shows that intention immediately precedes behavior. At the time a person thinks about becoming involved in a certain behavior, it remains an idea until there is an attempt that translates the intention into action. The attempt should result in success if the behavior is within the individual's volitional control (Ajzen, 1985, 2005). Ajzen (2005) also found that intentions correlate more strongly with behavior such that intentions provide a significantly greater predictive validity than that of attitudes. The review of the available literature supports the notion that specific behaviors can be predicted from the intentions to engage in the behavior.

Application of the TPB to Prior Studies. The TPB has been employed to study users' intentions in different areas, for example, in the adoption of new technologies (Morris & Venkatesh, 2000), in consumer behavior (Liao, Chen, & Yen, 2007), and in travel (Tsai, 2010). These three relevant studies are discussed in more detail.

Morris and Venkatesh (2000) used the TPB to study the effects of age in technology adoption decisions by workers during the course of their introduction to a new software system. Their study identified prior literature (Czaja & Sharit, 1993; Rhodes, 1983) that had also supported the notion that a fuller understanding of age differences in work attitudes and technology acceptance decisions was necessary. The results from their study showed that the greater influences among younger workers were from the attitudes toward using the technology, while the older workers' influences derived more from subjective norms and perceived behavioral control. They suggested that senior management should conduct user-analysis to ascertain the expected impact of new technology on workers, while training programs for new technologies should be structured with consideration given to the two separate groups of workers (Morris & Venkatesh, 2000). Their study is relevant to this study because of its focus on technology adoption decisions.

In their study, Liao et al. (2007) used the TPB as part of an integrated model to understand consumer's behavior regarding the ongoing usage of an online e-learning system. They collected data from users of a university e-learning system (n = 469) and used structural equation modeling (SEM) analysis to examine the relationships based on constructs of the expectation disconfirmation model and the TPB. The results from their study showed that subjective norms and perceived behavioral control were two important factors that significantly influenced an individual's behavioral intentions toward the continued use of online services. Among the measures they suggested for increasing customers' use of online systems were advertisements, propaganda, and the use of periodic reviews (Liao et al., 2007). The results are also consistent with similar studies that used the TPB to understand consumers' intentions and behaviors in the field of information systems (Mathieson, 1991; Taylor & Todd, 1995).

The study by Tsai (2010) applied the TPB to explore the behavior of independent travelers (i.e., people who travel on their own itinerary). His study presented a comprehensive set of hypotheses based on existing literature on relationships between TPB variables (Ajzen & Driver, 1992; Godin, 1994; Hrubes, Ajzen, & Daigle, 2001; Ryu, Ho, & Han, 2003; Wu & Lin, 2007). He then proceeded to examine belief factors influencing behavioral intention using three aspects: attitudes, subjective norms, and PBC. The sample for the study (n = 316) focused on Taiwanese who had experiences in independent travel. He found strong relationships between the variables of the TPB and an individual's willingness to engage in independent travel. The results also showed that perceived behavioral control had the greatest effect, but attitudes and subjective norms also had significant effects on the behavior intention of participants engaging in independent travel. He recommended that airlines, hotels, and bed-and-breakfast industries should establish favorable perceptions and provide more detailed travel information on the benefits of independent travel (Tsai, 2010).

Limitations of the TPB. Despite the widespread use of the TPB, some limitations were identified by researchers. Hardeman et al. (2002) carried out a systematic review to check the effectiveness of the TPB in situations that require behavior change interventions. They concluded that while the TPB was useful to measure process and outcome variables and was also useful to predict intention and behavior, it was less useful to develop behavior change interventions (Hardeman et al., 2002). In their study of health-related behaviors, McEachan, Conner, Taylor, and Lawton (2011) acknowledged the usefulness of the model but found that it did not provide specific guidance on change techniques. They also found that because of the length of follow-up from the time the TPB variables were measured and the subsequent measurement of the behavior, the predictive accuracy of the TPB was significantly lower with studies that used a longitudinal design (McEachan et al., 2011).

In the same manner, while Morris, Venkatesh, and Ackerman (2005) acknowledged that the TPB's prediction of variance was between 41%–50% of intentions and between 28%–34% of behaviors, there is still a significant amount of variance that remain unexplained (Armitage & Conner, 2001). Similar studies have also noted that the figures were obtained using self-reported measures, and predictions are superior to observed behaviors (Armitage & Conner, 2001; Conner & Armitage, 1998).

The limitations and the unexplained variances can be helped by the addition of other variables to supplement the TPB variables. Ajzen (1991) appeared to have recognized this when he noted that the TPB was open to additional predictors beyond the current ones. He further noted that, in theory, the predictors just need to sufficiently record a significant amount of the variances. This was also corroborated by the study of Conner, Sheeran, Norman, and Armitage (2000), who suggested that the inclusion of additional variables and moderator variables can help to address the unexplained variances in the TPB.

Some of the additional variables that have been shown to explain additional proportions of the variance include past behaviors/habits, moral norms, self-identity, belief salience, and affective beliefs (Conner & Armitage, 1998). The additional predictors that were used in this study were selected as possible factors that could influence a person’s intentions.

To conclude this section, a summary of the TPB’s limitations as provided by LaMorte (2018a) follows. He noted that the TPB does not consider other variables that could be factored into behavioral intentions and motivation, for example, fear, threat, mood, or experience. He also noted that the TPB does not consider the time frame between the intention and the behavioral action and does not address actual control over behavior. Finally, the TPB does not consider any environmental or economic factors that could influence a person's intention to perform a behavior (LaMorte, 2018a).

Application of the TPB to the Current Study. The review of the literature on the applications of the TPB found that the TPB could be successfully applied to this study since this study focused on the understanding of consumers’ behaviors. Therefore, the current study explored the extent to which the factors of the TPB can influence passengers’ intentions to use biometric technologies at airports. This study also examined how passengers' privacy concerns moderate the TPB factors that influence passengers' behavioral intentions. Perceived ease of use and perceived usefulness were also included as additional factors based on the studies that suggested the factors could influence individuals' attitudes and use of new technology (Curran & Meuter, 2005; Hung & Chang, 2005; Legris, Ingham, & Collerette, 2003; Lu, Chou, & Ling, 2009; McCloskey, 2006). The next section reviews the additional factors that were included with the factors of the TPB to study passengers' intentions to use biometrics at airports.

Factors Influencing Passengers' Intentions

The rationale for the selection of the additional factors was to consider previous research and to include any observable factors that could influence passengers' intentions. Since the components of the TPB have been discussed in the preceding sections, this section provides explanations and justification of the additional factors.

Perceived Ease of Use. Perceived ease of use has been postulated as a variable that could influence users' acceptance of a technology or system. Davis (1989) described perceived ease of use as the extent to which a user believes that using a particular system would require minimal effort. Perceived ease of use is one of the two key variables that deal with user acceptance in the technology acceptance model (TAM), the other being perceived usefulness. The TAM, as postulated by Davis et al. (1989) consists of six distinct but causally related variables, namely: external variables, perceived ease of use, perceived usefulness, attitude toward using, behavioral intention to use, and actual system use. TAM seeks to explain how users of a technology use and understand the technology.

In their study of user acceptance of computer technology, Davis et al. (1989) established that perceived ease of use was an important determinant of people's intentions to use computer technology. Although perceived ease of use was initially focused on the use of an information technology system, several studies have utilized perceived ease of use as a variable to examine attitudes and behavioral intentions to use different forms of technology. Examples include Lu et al. (2009), where the variable was used to investigate passengers' intentions to utilize airport self check-in stands, Smith et al. (2013), where it was used to examine the role of culture in influencing online shopping behavior, and Morosan (2014), where it was used to examine air travelers' use of mobile phones to purchase ancillary air travel services. Other studies are Vakilalroaia and Fatorehchi (2015), where it was used to understand passengers' willingness and tendencies to purchase air travel tickets electronically, Weng, Zailani, Iranmanesh, and Hyun (2017), where it was used to investigate users' continuous usage intention of a mobile taxi booking application service, and Panagiotopoulos and Dimitrakopoulos (2018), where it was used to investigate consumers' intentions toward autonomous vehicles.

Bradley (2009) noted that perceived ease of use will lead to attitude toward use, then to behavioral intention to use, and finally to actual use. Therefore, perceived ease of use was selected as a variable because it is suggested that passengers should be favorably inclined to use biometrics if they perceived that using biometrics would be easier to use than any current system presently in use.

Perceived Usefulness. Perceived usefulness is the second key construct of the TAM that deals with user acceptance. It was described as the extent to which an individual believes that using a particular system would augment the individual's job performance (Davis, 1989). Although the definition considers the usefulness of a system within an organizational context, several studies have examined perceived usefulness in the context of behavioral intentions and user acceptance of technology in general. Examples include Curran and Meuter (2005), used to investigate the adoption of three types of self-service technologies, Porter and Donthu (2006), used to explain differences in Internet usage among different demographic groups, and Hung and Chang (2005), used to investigate user acceptance of wireless application protocol (WAP) services.

Davis (1989) noted the significant relationship between perceived usefulness and user acceptance of technology systems and therefore recommended its inclusion in the design and implementation stages of such systems. In the same manner, Davis et al. (1989) suggested that usefulness could be more significant than ease of use and therefore should not be overlooked from research into user acceptance of technology. Perceived usefulness was included in this study as it was suggested that passengers will be likely to adopt the use of biometrics if they perceive that using biometrics would be advantageous for them.

While the TAM is not the specific focus of this study, the review from the studies referenced in this section showed that both perceived ease of use and perceived usefulness were significant factors that determined user acceptance of technologies. The two variables were thus included in this study due to their relationship with behavioral intention to use.

Privacy. Privacy concerns can be considered from two perspectives - information privacy and personal privacy. Information privacy refers to an individual's ability to control their own personal information and the extent to which details of the information are exchanged with other persons or systems (Hong & Thong, 2013). Personal privacy, on the other hand, considers discomforts that could be inherent from a person's cultural, religious, or personal beliefs (Nanavati et al., 2002). Regarding biometric systems, concerns due to information privacy are usually addressed through system policies, while personal privacy concerns are more individual in nature (Nanavati et al., 2002). Three different studies selected from some of the available literature that reviewed the privacy concerns of individuals and their attitudes and intentions toward the use of biometrics are reviewed below.

First, the study by Ngugi, Kamis, and Tremaine (2011) investigated users' intentions to use biometric keypad bank Automated Teller Machines (ATMs) that utilize user typing patterns to verify users' identity. The study involved a college student population (*n* = 159), as it was felt that college students were normally early adopters of technology and that their attitudes toward biometrics would be a good predictor of technology adoption. The privacy construct in their study, called system invasiveness, considered privacy from the collection of personal behavior patterns. The results from their study confirmed that high perceived system invasiveness will result in poor behavioral intention to use the biometric system, and recommended that for new biometric technologies to be accepted by users, the biometric system should be accurate, secure, trusted, and non-invasive (Ngugi et al., 2011).

Second, Kim and Bernhard (2014) investigated the factors that influenced hotel customers' intentions to use fingerprint technology as part of a biometric system. The sample (*n* = 526) was collected using panel members from the online survey company. Results from the study affirmed that higher privacy concerns about a fingerprint system decreased the users' intentions to use the technology. They suggested that to increase acceptance levels and to reduce personal concerns with the use of biometrics, organizations should explain the workings of biometric systems to customers and provide trial periods of biometric use (Kim & Bernhard, 2014).

Third, privacy concerns with the acceptance and use of biometric technologies were also assessed in the study by Carpenter, McLeod, Hicks, and Maasberg (2018). Their study sought the opinions of employees (n = 309) whose employing organization had deployed a new biometric system designed to keep track of employees' duty and to improve personnel safety. Although they acknowledged that privacy concerns could differ depending on the type of biometric system used (in this case fingerprint technology was used), the results from the study showed that privacy concerns were important determinants of employees' attitudes toward biometrics (Carpenter et al., 2018).

Privacy is an important concept to consider in discussions about biometrics because biometrics involve personal characteristics of the human body. Furthermore, individual perceptions and reactions to biometrics are likely to change as biometric technologies evolve. Overall, information privacy is likely to be more critical to individuals in the deployment of biometric technologies (Nanavati et al., 2002).

This section reviewed three studies that utilized the additional factors that were included in the TPB for this study. Although there are relationships between the three constructs of the TPB (Ajzen, 1991), these relationships were not tested in this current study. The next section reviewed studies of passengers' use of biometrics and their privacy concerns with the use of biometrics.

Studies of Passengers' Use of Biometrics

The use of biometrics in the identification and verification of persons has been demonstrated in studies covering sectors such as medical and health (Brown, 2012;

Caldwell, 2015; Flores Zuniga, Win, & Susilo, 2010), banking (Ahmad & Hariri, 2012; Fatima, 2011), hotel and hospitality (Kim & Bernhard, 2014; Ko & Yu, 2015; Murphy & Rottet, 2009), retail (Clodfelter, 2010; Li & Hwang, 2010), and in crime investigation and justice (Bustard, Carter, Nixon, & Hadid, 2014; Emami et al., 2016). This section focused on studies that involve passengers' use of biometrics at airports.

Some of the available studies of passengers' use of biometrics at airports that are relevant to this research have focused on passenger privacy and security (Merlano, 2016; Moradoff, 2010; Morosan, 2012a, 2012b, 2018; Neo et al., 2014; Pranic, Roehl, & West, 2009), and on enhancing overall passenger experience (Farrell, 2016; Gohringer, 2012; Költzsch, 2006; Morosan, 2018). Prior studies have also projected the development of biometrics through the focus on standards and technical requirements for biometrics (Entwistle, 2006; Grother, 2008; Kochan, 2004).

The central issues that could affect the use of biometrics by passengers appear to be linked to concerns over individuals' privacy, security, and protection of their data. For example, Neo et al. (2014) examined privacy from the perspectives of tourists arriving into Malaysia. The study involved a survey of international tourists (n = 331) and used SEM analysis to investigate inbound tourists' satisfaction with the mandatory provision of fingerprint data. Two types of privacy were included among the constructs examined in the study. These are information privacy, which deals with disclosure of information to third parties, and physical privacy (or personal privacy), which is related to any perception of harm that could cause users' reluctance to the use of biometrics. It was found that information privacy was a significant construct that could affect tourists' satisfaction; it was thought that this could be due to the users' concerns about biometric data being provided to other parties. Conversely, physical privacy did not significantly affect tourists' satisfaction, probably due to the mandatory requirements to provide biometrics by users and by the fact that users had no options to decline the provision (Neo et al., 2014).

In the area of personal security at airports, Pranic et al. (2009) examined travelers' acceptance of biometric technologies in airport security procedures. Their survey (n = 558) of visitors to a tourism marketing website collected information on respondents' acceptance and effectiveness of biometric strategies. Results from their study showed that travelers found the use of biometric features such as fingerprints, eye scans, and face scans acceptable as part of security measures. Because these biometric features were linked to databases, it appears that travelers were willing to trade information privacy for personal safety (Pranic et al., 2009). Studies also show that passengers generally consent to waive certain privacy rights to facilitate expedited screening (Merlano, 2016, Morosan, 2018, Pranic et al., 2009). The present study examined a wider view of factors that the literature suggests affect passengers' intentions to use biometrics at airports.

Moradoff (2010) reviewed privacy and human rights issues with the use of biometrics. He noted that although the United States Privacy Act of 1974 limits the collection, use, and disclosure of personal information by federal agencies, the Act includes exceptions for law enforcement and national security purposes. He, therefore, suggested that further debates are necessary around civil liberties, human rights, and the 'democratic deficit' that may come about from the use of biometrics. These debates should help to attain a balance between security and privacy in the use of biometrics (Moradoff, 2010).

Other studies of passengers' use of biometrics addressed the requirements for passenger security and privacy along with the provision of efficient passenger handling and control services. A review of the applications of biometric technologies in aviation security programs completed by Költzsch (2006) noted that any future aviation security approach should integrate biometric technologies with other airport processes and infrastructure in a manner that ensures optimization of the passenger clearance process. A later report on one aspect of biometric technology by Gohringer (2012), found that the usage of facial recognition technology in airports allowed the automation of immigration procedures and processes, enhanced surveillance and security, enabled seamless passenger travel, and facilitated the gathering of valuable statistical information pertaining to passenger movements. He identified a long-term goal that involves the assignment of a single biometric identifier to a passenger which can subsequently be used to cover the entire itinerary at the airport - from booking to check-in, baggage drop, transit through security checks, and eventually to boarding the aircraft (Gohringer, 2012).

Along the same lines, Farrell (2016) reviewed the requirements for a high level of security with passengers' need to get through the airport as easily as possible. He suggested the use of biometric technologies in end-to-end passenger self-service systems at airports. He also noted that airports should integrate biometric technologies with legacy airline and airport business processes and systems and with external systems such as government watch lists (Farrell, 2016).

Another study on passengers' use of biometrics that was reviewed in this section was by Morosan (2018). He examined the impact of travelers' general privacy concerns and perceived security on the biometric information disclosed to electronic gates (e-gates). His study utilized a survey (n = 511) of U.S. travelers that had taken a commercial aviation trip in the 12 months period prior to the study. Results from the study showed that while perceived security was the strongest determinant of travelers' willingness to disclose information to e-gates, the general privacy concerns of travelers had only a modest impact on their willingness to disclose information (Morosan, 2018). One of the recommendations from his study was a suggestion for future study to include additional behavioral variables to understand consumer's disclosure behaviors. This present study included perceived ease of use, perceived usefulness, and privacy concerns as additional factors that have been suggested to influence passengers' intentions and behaviors.

Notwithstanding the security and privacy issues identified in the studies reviewed, concerns about the adequacy of current privacy protections in the use of biometric data appear to have been addressed by the Privacy Impact Assessment (PIA). A PIA is a systematic process whereby organizations or governments evaluate the potential effects of a project or initiative on individuals' privacy (Clarke, 2009). The use of PIAs has been examined by several studies (Wadhwa, 2012; Wadhwa & Rodrigues, 2013; Wright, 2013; Wright et al., 2014), and it appears to be an acceptable solution that benefits the main parties and should, therefore, be considered in discussions on the adoption of biometric technologies. While governments and private enterprises use PIAs to encourage the adoption of potentially privacy-intrusive technologies, privacy advocacy groups use PIAs to ensure new technologies are designed from the onset with features that reduce privacy intrusion (Clarke, 2009; Moradoff, 2010).

The current section reviewed studies of passengers' use of biometrics. While the main issues appear to have been considered as they relate to passengers' privacy, security, and protection of data, the present study introduced additional variables to help understand passengers' intentions to use biometrics. The following section presented the theoretical framework and hypotheses for the present study.

Theoretical Framework and Hypotheses

The theoretical framework for a study was described as an *a priori* (resulting from theoretical deduction) research plan that highlights and details the major elements, variables, and constructs which help organize and focus the research study (Abend, 2008; Ennis, 1999; Ngulube, Mathipa, & Gumbo, 2015). Following the summary of the relevant literature as presented in the earlier sections, the current study suggested a theoretical framework as seen in Figure 2, which shows attitudes, subjective norms, perceived behavioral control, perceived ease of use, perceived usefulness, and privacy concerns as independent variables. The framework also shows passengers' behavioral intentions to use biometrics as the dependent variable. The selection of the dependent variable was justified from Ajzen (1991), who noted that the best predictor of technology use is the behavioral intention to use the technology.

The operational definitions of the study constructs and variables are presented in Table 4. The study also includes the collection of respondent's demographic data such as age, gender, level of education, ethnicity, and annual total income.

Figure 2

Research Theoretical Framework and Hypotheses

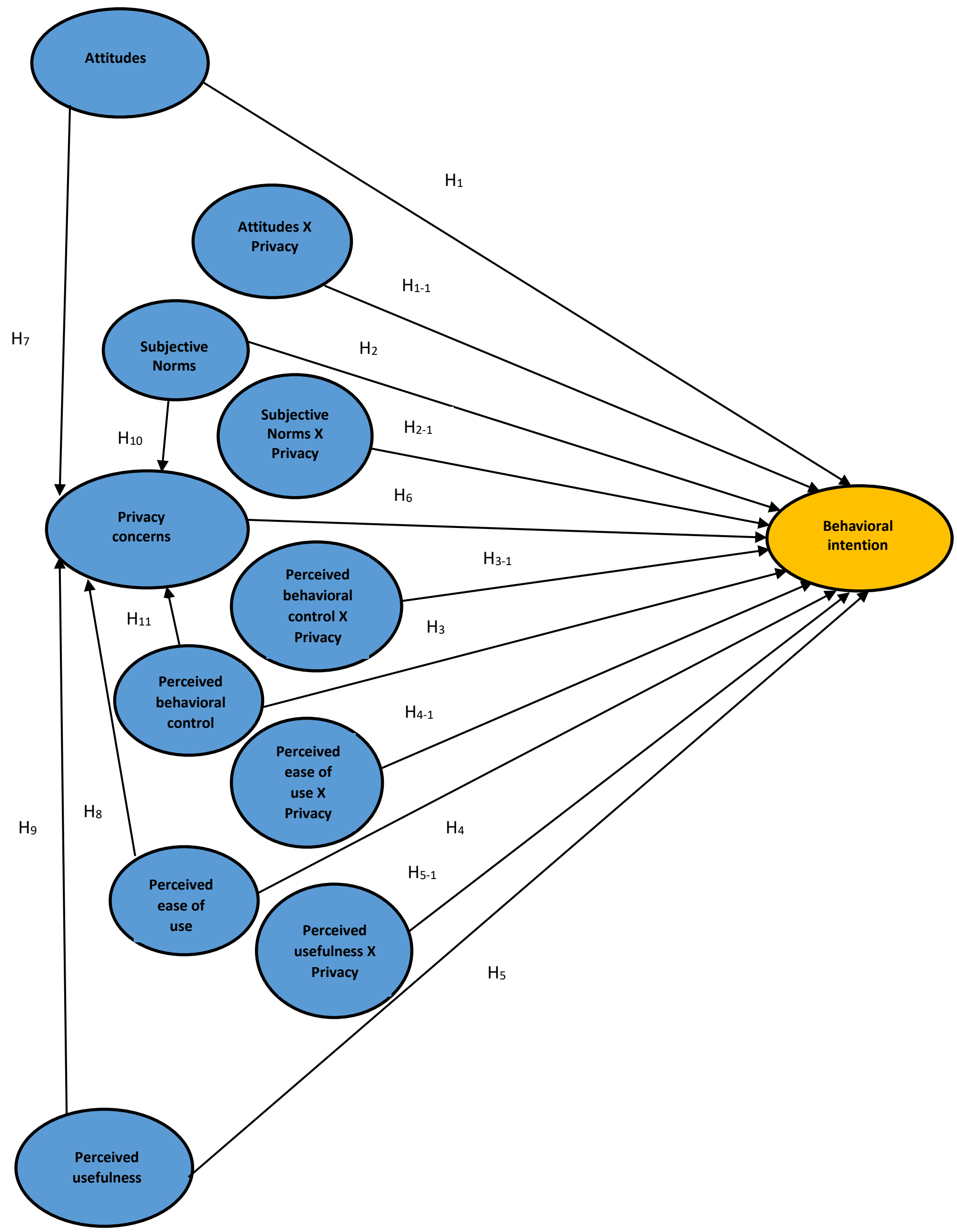


Table 4

Operational Definitions of Constructs/Variables

Construct/Variable	Operational Definition/Description
Attitudes	A passenger's positive or negative feelings about using biometrics
Subjective Norms	A passenger's perception that most people important to the passenger think that the passenger should or should not use biometrics
Perceived Behavioral Control	A passenger's perception of the control regarding the decision to use biometrics
Perceived Ease of Use	The degree to which a passenger believes that using biometrics would be free of effort
Perceived Usefulness	The degree to which a passenger believes that using biometrics would be advantageous for them
Privacy concerns	A passenger's perception of the collection, use, and management of the passenger's personal information while using biometrics
Intention to Use	A passenger's intentions to use biometrics

The independent variables are attitudes, subjective norms, perceived behavioral control, perceived ease of use, perceived usefulness, and privacy concerns, while the dependent variable is the intention to use. Privacy was also studied as a moderating variable on the other independent variables. These variables are latent variables and therefore cannot be directly observed. These latent variables were measured by manifest variables that were assigned to each latent variable. The manifest variables are all questions that were directly measured with a five-point bipolar scale. The latent variables, the number of question items associated with the manifest variables, and the sources for the question items are shown in Table 5. Additional details for the question items are also shown in Appendix C.

Table 5

Number of Items and Sources for Measurement of Latent Variables

Latent Variables	Number of Items	Sources
Attitudes	4	Chen, Fan, and Farn (2007); Taylor and Todd (1995)
Subjective Norms	3	Chen, Fan, and Farn (2007); Reza Jalilvand and Samiei (2012); Taylor and Todd (1995)
Perceived Behavioral Control	3	Taylor and Todd (1995)
Perceived Ease of Use	4	Lu, Chou, and Ling (2009); Wang, Wang, Lin, and Tang (2003)
Perceived Usefulness	3	Lu, Chou, and Ling (2009); Wang, Wang, Lin, and Tang (2003)
Privacy Concerns	3	Albashrawi and Motiwalla (2017); Hong and Thong (2013)
Intention to Use	3	Al Ziadat (2015); Lu, Chou, and Ling (2009); Wang et al. (2003)

The framework for this study considered the relationships between the independent variables and intentions instead of the typical TPB model that focuses on the relationships between the independent variables, intentions, and actual behavior. This study was also limited by scope to the direct relationships between the independent variables and intentions and did not consider any other relationships that may exist between the variables. The following statements present the hypotheses for the study based on the framework.

The definition of attitude connotes a strong link between attitude and behavior. It also implies that if a person's attitude could be measured, then it should be possible to explain and predict the person's behavior (Fishbein & Ajzen, 1975). Other studies have suggested that different attitudes can cause different types of behaviors (Ajzen &

Fishbein, 2000; Bentler & Speckart, 1981; Glasman & Albarracín, 2006; Koestner, Bernieri, & Zuckerman, 1992; Rodríguez-Barreiro et al., 2013).

With the positive relationship theorized from the available literature and the need to investigate the relationship between attitudes and passengers' intentions to use biometrics at airports, H_1 was proposed for the study. $H_{1\text{-}1}$ was also proposed to assess the moderating influence of privacy concerns on passengers' attitudes.

H_1: Attitudes positively influence passengers' intentions to use biometric technologies at airports.

$H_{1\text{-}1}$: The level of privacy concerns will moderate the positive relationship between passengers' attitudes and intentions to use biometric technologies at airports.

Subjective norms relate to a person's perception of the social pressures put on the person to act in a certain manner in respect to a specific behavior. An individual will perceive social pressure to perform a behavior if there is a belief that the people most influential according to the individual (referents) feel that the behavior should be carried out. Conversely, if the individual believes that most referents think that the behavior should not be performed, then there is a subjective norm that puts pressure on the individual to shun the behavior (Ajzen, 1985). While some studies have found that subjective norms significantly influenced an individual's intentions to perform a given behavior (Liao et al., 2007; Tsai, 2010), there are other studies that did not consider the effect of subjective norms significant enough to influence intentions (Karahanna et al., 1999; Van Slyke et al., 2007). In the area of biometrics, Seyal and Turner (2013) found that subjective norms positively influenced behavioral intention to use biometric technology among executives in Brunei, while Kim and Bernhard (2014) found subjective norms as one of the factors that significantly influenced hotel customers' intentions to use fingerprint technology. From the review of the studies, a positive relationship was hypothesized for this study. Therefore, H_2 was proposed for the study while H_{2-1} was also proposed to assess the moderating influence of privacy concerns on subjective norms.

H_2: Subjective norms positively influence passengers' intentions to use biometric technologies at airports.

H_{2-1}: The level of privacy concerns will moderate the positive relationship between subjective norms and intentions to use biometric technologies at airports.

Ajzen (1985, 2002) noted that notwithstanding the effects of any other factors, a high level of PBC should strengthen an individual's intention to perform the behavior and lead to an increase in effort and perseverance. He also investigated the contribution of PBC in evaluating behavioral intention of individuals through the interaction with attitudes and subjective norms. While PBC can affect behavior directly or indirectly, it can be used as an additional direct predictor of behavior (Ajzen, 2002). The review of the literature identified studies that examined the effects of PBC on individual's intentions (Armitage & Conner, 1999; Lee, 2016; Soon & Wallace, 2017), and showed researchers that specified a positive relationship between PBC and intentions (Mathieson, 1991; Shih & Fang, 2004; Taylor &Todd, 1995). Therefore, H_3 was proposed to study the perceived behavioral control of passengers, while H_{3-1} was proposed to assess the moderating influence of privacy concerns on perceived behavioral control.

H_3: Perceived behavioral control positively influences passengers' intentions to use biometric technologies at airports.

H_{3-1}: The level of privacy concerns will moderate the positive relationship between perceived behavioral control and intentions to use biometric technologies at airports.

Perceived ease of use considers the belief of an individual in the effort required to use a system. Studies have examined the role of perceived ease of use as a factor in individuals' attitudes and use of new technology (Legris et al., 2003; Lu et al., 2009). Other studies found a positive and significant relationship between perceived ease of use and behavioral intention (Davis et al., 1989; Jackson, Chow, & Leitch, 1997; Szajna, 1996; Venkatesh & Morris, 2000). From the review of the literature and the need to examine the effect of perceived ease of use on passengers' intentions to use biometric technologies, H_4 was proposed for the study. H_{4-1} was also proposed to assess the moderating influence of privacy concerns on perceived ease of use:

H_4: Perceived ease of use positively influences passengers' intentions to use biometric technologies at airports.

H_{4-1}: The level of privacy concerns will moderate the positive relationship between perceived ease of use and intentions to use biometric technologies at airports.

Perceived usefulness is concerned with the perception of an individual about the extent to which using a particular technology would contribute to the fulfilment of certain tasks. Most of the studies that examined behavioral intentions and perceived ease of use also examined perceived usefulness (Davis et al., 1989; Legris et al., 2003; Lu et al., 2009). While Davis et al. (1989) found perceived usefulness to be a major determinant of people's intentions to use computer technology, Jackson et al. (1997) found a non-significant relationship between perceived usefulness and behavioral intentions to use an information system. Thus, H_5 was proposed for the study. H_{5-1} was also proposed to assess the moderating influence of privacy concerns on perceived usefulness:

H_5: Perceived usefulness positively influences passengers' intentions to use biometric technologies at airports.

H_{5-1}: The level of privacy concerns will moderate the positive relationship between perceived usefulness and intentions to use biometric technologies at airports.

Albashrawi and Motiwalla (2017) identified privacy concerns as a possible significant influencer on the usage of technology. Further studies reviewed have also suggested that an increased level of privacy concerns results in decreased intentions to use technology (Kim & Bernhard, 2014; Wang, Lin, & Luarn, 2006; Zhou, 2012). With the knowledge of the existing literature and the need to investigate the direct impact of privacy on passengers' intentions to use biometric technologies, H_6 was therefore proposed for the study:

H_6: Privacy concerns negatively influence passengers' intentions to use biometric technologies at airports.

Morosan (2012a) examined the relationship between travelers' perceived privacy and their attitudes toward registered traveler biometric systems from a technology acceptance viewpoint. His study found strong support for the hypothesis that travelers' perception of privacy positively influenced their attitudes toward registered traveler biometric systems. Other studies also supported the hypothesis that information privacy positively affected attitudes toward biometrics (Neo et al., 2016) and attitudes toward organizational practices in general (Smith, Milberg, & Burke, 1996).

Two other studies reversed the relationship between the variables but maintained the same meaning. The study by Joinson, Paine, Buchanan, and Reips (2006) found that privacy concerns resulted in negative attitudes toward the use of smart identity cards containing biometric information, while Carpenter et al. (2018) found that two constructs of privacy concerns (perceived accountability and perceived vulnerability) had negative effects on employees' attitudes toward biometrics. Based on the review of the literature, H_7 was proposed for the study:

H_7: Attitudes negatively influence passengers' privacy concerns toward biometric technologies at airports.

James, Pirim, Boswell, Reithel, and Barkhi (2006) considered privacy from the perception of physical invasiveness of a biometric system. They found a negative significant relationship between the perceived physical invasiveness of the biometric system and the perceived ease of use of the technology. More recently, Oh, Lee, and Lee (2019) evaluated ease of use as one of the factors of usability. Their study measured the overall user experience with biometric systems through technical, ergonomic, and psychological aspects. They found that privacy concerns were an important sub criterion when measuring the usability of biometric systems and suggested that reduced privacy concerns would improve the usability of the system (Oh et al., 2019). Other studies (Patrick, 2004; Sasse, 2005) suggested that the usability of biometric systems depends on the consideration of the risks to privacy against the benefits of providing the biometric data to the system. Thus, H_8 was proposed for the study:

H_8: Perceived ease of use negatively influences passengers' privacy concerns with the use of biometric technologies at airports.

Sasse (2005) noted that people's privacy concerns are normally secondary when a safety need is perceived. Furthermore, other studies have reported on the effect of privacy concerns on perceived usefulness (Kumar, Mohan, & Holowczak, 2008; Xu & Gupta, 2009; Zhou, 2015). Based on the available literature, H_9 was proposed for the study:

H_9: Perceived usefulness negatively influences passengers' privacy concerns with the use of biometric technologies at airports.

Taneja, Wang, and Raja (2006) hypothesized a relationship between subjective norms and privacy concerns. Subjective norms are said to be associated with a desire to be compliant because people tend to choose an action suggested by their important referents, regardless of what the individual believes (Kim & Bernhard, 2014; Schepers & Wetzels, 2007). Subjective norms could also result from the social influences of cultures and traditions. The study by Riley, Buckner, Johnson, and Benyon (2009) compared different cultures and found that there were differences in privacy concerns with the users of biometric technologies across the different cultures surveyed. The limited literature on this relationship and the need to examine it further resulted in H_{10} being proposed as a non-directional hypothesis for the study:

H_{10}: Subjective norms are related to privacy concerns with the use of biometric technologies at airports.

The available literature on a direct connection between the perceived behavioral control (PBC) of individuals and their privacy has focused on patients' privacy protection from the point of view of both patients and medical personnel. For example, Agaku, Adisa, Ayo-Yusuf, and Connolly (2014) showed that patients' perceived behavioral control of the decision to provide or withhold health information was related to their privacy concerns. On the other hand, Ma, Kuo, and Alexander (2016) found that nurses' PBC had a positive influence on their concerns about the privacy of patients' electronic medical records, while Tabak and Ozon (2004) found a positive relationship between nurses PBC and their actions to promote patients' privacy.

There is, however, limited research on the effect of PBC on individual's privacy with the use of biometric technologies. Thus, H_{11} was proposed for the study:

H_{11}: Perceived behavioral control is related to privacy concerns with the use of biometric technologies at airports.

Chapter Summary

The literature review covered the basic principles of biometrics and research into the use and acceptance of biometric technologies at airports. One of the major gaps identified from the review was related to the need to explore a more precise quantification of the extent of the relationships among the variables affecting passengers' adoption of biometric systems. The review also showed that continuous monitoring of passengers' attitudes was necessary to determine passengers' willingness to use biometrics.

Although the DIT and the TRA were considered as alternative theories for the study, the TPB was selected as the theoretical foundation. The literature review provided the justification for the selection of the TPB and for the inclusion of the additional variables in the study. From previous research, the TPB constructs of attitudes, subjective norms, and PBC were found to be significant determinants of passengers' intentions, while the key TAM constructs of perceived ease of use and perceived usefulness have been utilized as variables to examine attitudes and intentions. Appropriate studies from the literature were also provided in support of the selection of privacy as an additional variable that could affect passengers' behavioral intention.

While there were some differences from the conclusions in the studies that were reviewed, passengers' concerns about the use of biometrics were mostly related to privacy, security, and protection of data. It was suggested that having a study like this present one, with a broader view of factors, helped to understand passengers' intentions to use biometrics at airports. The next chapter presents a discussion of the research method, design, and the procedures used to test the hypotheses.

Chapter III: Methodology

This chapter begins with a description of the research approach, design, and procedures that are applicable to this study. It then presents details of the population, the sample, and the process of data collection and testing of hypotheses. The chapter also provides details of the research instrument that was used to obtain the data and addresses the ethical issues that were considered during the study. Finally, the chapter concludes with a description of methods of statistical treatment of data that allowed appropriate conclusions to be made.

Research Approach

The research approach of a study comprises the plans and procedures for the study and includes the steps from the initial assumptions of the study to the detailed methods of collection, analysis, and interpretation of data (Creswell, 2014). From this description, three possible research approaches are identified - qualitative, quantitative, and mixed methods approaches. Qualitative research refers to research carried out using words, quantitative research deals with the use of numbers, and mixed methods refer to a combination of both research approaches (Creswell, 2014).

Yilmaz (2013) noted that the main differences between quantitative and qualitative research are reflected in their assumptions, research purpose, approach, and in the role of the researcher. For example, quantitative research is informed by an objectivist epistemology, has a purpose of generalization, assumes variables can be identified and relationships measured, begins with theories and hypotheses, and considers the researcher's role to be etic (outsider's point of view). Qualitative research, however, is predicated on a constructivist epistemology, has a purpose of contextualization, assumes variables are complex, interwoven, and difficult to measure, ends with grounded theory or hypotheses, and considers the researcher's role to be emic, that is, insider's point of view (Yilmaz, 2013). Mixed methods research involves a combination of quantitative and qualitative research and data within a study either at the same time (parallel) or one after the other, that is, sequential (Creswell, 2014; Saunders, Lewis, & Thornhill, 2009).

This study followed a quantitative approach and utilized deductive reasoning logic to investigate the factors that influence passengers' intentions to use biometric technologies at airports. The quantitative approach selected for this study is appropriate as it was intended to generalize the results from the sample of the participants to the population. The quantitative approach was also selected because the research problem required the determination of factors that affect an outcome, and it is also considered the most appropriate approach to deploy for testing a theory (Creswell, 2014; Vogt et al., 2012). Furthermore, the study utilized the theory of planned behavior (TPB) as grounded theory, proposed hypotheses, identified other variables used in addition to the TPB variables, and measured the direct relationships between the variables.

Babbie (2013) also considered the research approach in terms of the thinking or reasoning that can provide a complete understanding of social phenomena. This classification identifies two types of research approaches – inductive and deductive reasoning. Inductive reasoning considers specific observations and moves to the discovery of a pattern or order, while deductive reasoning moves from a pattern that is expected by logic or theory to observations that test the occurrence of the pattern (Babbie, 2013). The deductive reasoning technique utilized in this study started with a theoretical framework (the TPB), derived hypotheses linking specific variables, and tested the hypotheses through empirical data to determine if the data supports the deductive expectations (Babbie, 2013).

Research Design

The research design of a study refers to the type of enquiry that provides the specific direction for the study (Creswell, 2014). In their classification, Vogt et al. (2012) identified six major types of research designs – surveys, interviews, experiments, observations, archival, and combined research designs. Although the choice of a type of research design is linked to the research problem and theories, the choice is also dependent on other factors including the researcher's personal preferences and experiences, time, cost, and availability of data (Saunders et al., 2009; Vogt et al., 2012). The choice of research design usually occurs at the beginning of the research study and is related to all other aspects of the research (Babbie, 2013).

This study was conducted using a correlational research design and a cross-sectional time horizon to investigate the factors that influence passengers' intentions to use biometric technologies at airports. The study involved the use of an electronic questionnaire as the survey instrument which was administered to participants, while structural equation modeling (SEM) techniques were employed as the statistical procedure for data analysis.

Correlational research involves the examination of naturally occurring variables to determine the relationships that exist between them as opposed to manipulating variables and observing their effects (Field, 2009). The correlational research design was selected because the researcher intended to obtain a natural view of the research questions without interfering or influencing the events. The survey instrument that was used in this study allowed the collection of numeric descriptions of the opinions of a sample of the population. The findings from the sample can then be generalized to the population. The use of the survey instrument works best when respondents provide data directly by giving brief answers to structured questions and when the respondents provide reliable information (Vogt et al., 2012). The survey instrument used in the current study is an electronic questionnaire, and it was designed to ensure that questionnaire items are clear and unambiguous (Babbie, 2013).

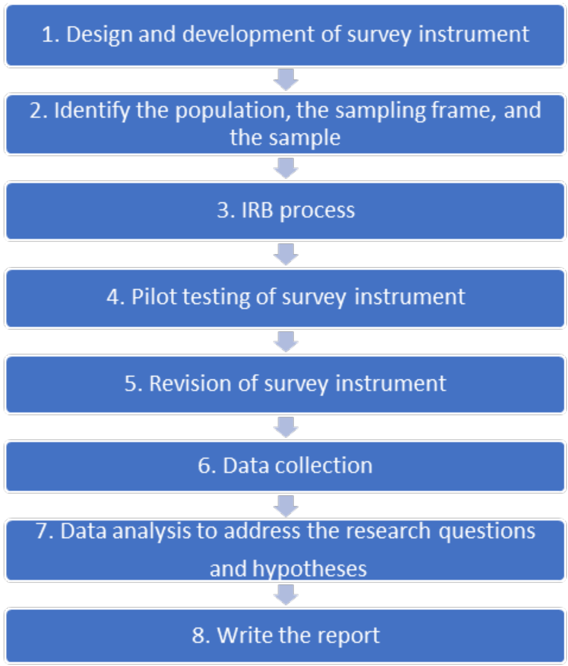
The time horizon for the research could be done either as a ‘snapshot’ horizon taken at a particular time (cross-sectional) or as a series of snapshots over a given period, that is, longitudinal (Saunders et al., 2009). This study was completed as a cross-sectional study using an electronic questionnaire for data collection to investigate the factors that influence passengers’ use of biometrics. A cross-sectional time horizon for this study was considered the best value for both money and time required, as data was collected only once, and time is not an important variable in the study (Vogt et al., 2012).

Research Procedures

The procedure that was followed to conduct this study includes the following steps: questionnaire design, sample selection, and data collection (Babbie, 2013). Other steps in the procedure involve the completion of the Institutional Review Board (IRB) process, pilot testing of the questionnaire, identification of potential ethical issues, and completion of data analysis procedures to provide responses to the research questions and hypotheses. There were eight steps in conducting this research, as summarized in Figure 3.

Figure 3

Steps in Conducting Research



The correlational design and cross-sectional time horizon selected in this study involved the administration of an electronic questionnaire to participants. The questionnaire was developed using Google Forms ® and presented electronically to participants via the Amazon ® Mechanical Turk ® system (MTurk) hosting platform. A screening criterion that was specified is that only participants currently registered as MTurk workers from the United States were eligible to participate in the study. First, participants were requested to confirm their participation in the study by acknowledging an electronic informed consent form. They were then provided with instructions for completing the questionnaire and reminded that they could decide to discontinue the questionnaire at any time.

The questionnaire included questions with options based on the variables in the study; participants were thus required to select their responses to the independent (exogenous) variables and the dependent (endogenous) variable on 5-point Likert-type scales. Once the questions were completed, the final section contained a message to thank the participants and a request for them to insert a code to enable them to receive a monetary compensation. The compensation amount did not exceed 50 U.S. cents per participant, as suggested by Buhrmester, Kwang, and Gosling (2011).

Population and Sample

Population and Sampling Frame. The population in a research study refers to the group of persons who have the same characteristic, while the target population is the population within this group that a researcher can identify and study (Babbie, 2013; Bell, 2005; Creswell, 2012). The target population in this study were residents of the United States that are 18 years of age or older. As it would be impractical and time-consuming to survey the entire target population, a sampling frame was selected as a subset of the target population. The sampling frame in this study were the participants that were available to complete human intelligence tasks (HITs) from MTurk.

The MTurk system was launched by Amazon in 2005 as an online crowdsourcing system that allows task owners (known as requesters or employers) to distribute micro tasks to anonymous employees (known as workers or contractors) for a small reward (Bartneck, Duenser, Moltchanova, & Zawieska, 2015). The availability of MTurk has provided researchers the opportunity to recruit a diverse pool of study participants for a minimal fee per participant (Antoun, Zhang, Conrad, & Schober, 2016; Johnson & Borden, 2012), leading to overall cost and time savings for a research study. It is an example of a 'pull in' service that allows researchers to find participants online that consent to the completion of tasks for compensation. Several studies (Horton, Rand, & Zeckhauser, 2011; Mason & Suri, 2012; Rice et al., 2017) also confirmed the usefulness of MTurk to researchers in the conduct of studies in the social sciences.

Since this present study sought to assess the behavioral intentions of passengers toward the use of biometrics, three studies that utilized an MTurk sample in assessing consumer behavioral intentions were reviewed in this section. First, Makki, Ozturk, and Singh (2016) used a sample from MTurk (*n* = 412) to study consumers' behavioral intentions toward mobile payment (MP) systems based on near-field communication (NFC). While they acknowledged that the results from the study might not be generalizable to all categories of MP users, their analysis of the study's respondents concluded that the sample adequately represented the population of interest (Makki et al., 2016).

Secondly, Okumus, Bilgihan, and Ozturk (2016) investigated consumers' intentions to use smartphone diet applications (apps) when ordering food and beverages at foodservice businesses. In their justification for the use of a sample from MTurk (*n* = 395), they noted that while MTurk participants are generally younger than the public, the sample contains the major elements required in a research study. They also concluded that the MTurk sample can be used to obtain high-quality data (Okumus et al., 2016).

The third study reviewed was completed by Song, Kim, and Cho (2018). The authors used a sample from MTurk (*n* = 236) to investigate users' continuance intentions to use smart-connected sports products. Although they noted that certain demographics (for example, education level) of workers may limit the appropriateness of target participants in the study, they acknowledged the feasible user base provided by MTurk and suggested further research to include collecting data in different settings (Song et al., 2018).

Further justification for the use of an MTurk sample against other forms of samples was provided by Bartneck et al. (2015) who compared responses received from MTurk participants and from online or on-campus direct recruitment of participants. Their study used LEGO® Minifigures and requested participants to evaluate the facial expressions of 94 different LEGO® Minifigures. Although they reported a statistical difference between the results from the Mturk participants and the results from the online or on-campus participants, they noted that the difference was small and did not have any practical consequence (Bartneck et al., 2015). A similar study by Steelman, Hammer, and Limayem (2014) found that U.S. online crowdsourcing markets (OCMs) such as MTurk are a viable and alternative sampling frame for the recruitment of U.S. participants (Steelman et al., 2014).

In terms of representativeness, respondents on MTurk are adjudged to represent a closer sample of the U.S. population as a whole than persons sampled from traditional university subject pools (Paolacci et al., 2010). Berinsky et al. (2012) also reported that the demographic characteristics of MTurk participants have been shown to be a closer representation of the U.S. population demographics when compared to in-person convenience samples. With the evidence to show that data from self-selected web participants can be considered valid just like normal laboratory data (Buhrmester et al., 2011; Germine et al., 2012), the MTurk system was thus selected to provide the sampling frame for this study.

Sample Size. The sample for a study is the subgroup within the target population chosen to generalize results to the target population (Creswell, 2012). The sample utilized in this present study was a convenience sample from MTurk. Vogt et al. (2012) advised that the two criteria for selecting from a pool of respondents are that respondents in the study should be able and should also be willing to participate. The use of a convenience sample from MTurk in this present study satisfies these two criteria. Although the use of a convenience sample may limit the representativeness of the population, it provides valuable information that could be used to answer research questions and hypotheses (Creswell, 2012), while also allowing for the collection of a larger sample size for the study at a relatively low cost.

The minimum size of the sample for a study is influenced by factors such as sampling error, number of variables, type of statistical procedure, and confidence in the statistical tests to be employed (Creswell, 2012). For studies utilizing SEM analysis, it is generally accepted that using a large sample size should help minimize the possibility of standard errors and technical problems occurring in the analysis (Kline, 2011). In their assessment, Hair, Black, Babin, and Anderson (2015) noted the greater sensitivity of SEM to sample size when compared to other multivariate approaches. They also provided some important parameters to consider in the determination of a minimum sample size for an SEM study. These are multivariate normality, estimation technique, model complexity, missing data, and the average error variance. Their suggestion is for a minimum sample size of 300 persons for a model with seven or fewer constructs (Hair et al., 2015).

In another opinion regarding minimum sample size for SEM, Jackson (2003) recommended that the minimum sample size should be thought of in terms of the ratio of cases (*N*) to the number of model parameters that require statistical estimates (*q*), and proposed an ideal *N:q* ratio of 20:1 (Jackson, 2003). On her part, Iacobucci (2010) suggested a sample size of between 50-100 was sufficient for a good SEM model. Reporting on the use of rules of thumb to determine sample size, Wolf, Harrington, Clark, and Miller (2013) noted that such rules could result in the overestimation or underestimation of sample size requirements, and thus suggested the use of Monte Carlo Analyses for sample size determinations (Wolf et al., 2013). Similarly, MacCallum, Widaman, Preacher, and Hong (2001) favored the use of the level of communalities (which is the average variation existing among the variables) over the traditional rules of thumb for determining minimum sample size.

Another method used to determine the minimum sample size in SEM was proposed by Westland (2010). His method involves the use of an algorithm that considers the ratio of the number of indicator variables to the number of latent variables, the minimum effect, power, and significance values specified for the study. His review of a sample of 74 articles to determine the adequate sample size using his calculation technique concluded that more than 80% of the research articles drew conclusions from insufficient samples. Although he acknowledged that there are many factors that can affect sample size in a structural equation model, his method resulted in larger sample sizes than other standard sampling methods.

The formula to calculate minimum sample size, *n,* as stated by Westland (2010), is presented in equation 1.

$$n = \frac{1}{2H}\left(A\left(\frac{\pi}{6} - B + D\right) + H + \sqrt{\left[A\left(\frac{\pi}{6} - B + D\right) + H\right]^2 + 4AH\left(\frac{\pi}{6} + \sqrt{A} + 2B - C - 2D\right)}\right) \quad (1)$$

where:

$$A = 1 - \rho^2$$

$$B = \rho\text{arcsin}\left(\frac{\rho}{2}\right)$$

$$C = \rho\text{arcsin}(\rho)$$

$$D = \frac{A}{\sqrt{3 - A}}$$

$$H = \left(\frac{\delta}{z_{1-\alpha/2} - z_{1-\beta}}\right)^2$$

This study utilized an online sample size calculator by Soper (2019) to determine the minimum sample size requirement for the SEM analysis. The online calculator is based on the formula by Westland (2010) and provides a method to determine the sample size given the effect size and the desired power level. This method is also practical and expeditious, especially considering the complexity of the Westland (2010) formula. The sample size, *n,* effect size, $f^{2,}$ power level, 1-β, and significance level, α, are all statistical properties that are related such that once any three are known and fixed, the remaining one can be determined (Cohen, 1988; Field, 2009).

The effect size of a study is the extent to which the phenomenon exists in the population (Cohen, 1988). It provides an objective means of comparing the magnitudes of observed effects across separate studies that measure different variables, or use different scales of measurement (Field, 2009). The widely used suggestion by Cohen

(1988) indicates that an effect size of 0.1 is considered small, 0.3 is medium, and 0.5 is large (Cohen, 1988). An effect size of 0.2 (small to medium) was used in this study. With this effect size, it was expected that the effect explained 4% of the total variance.

The statistical power of a test is the probability that a given test will result in an effect, provided an effect exists in the population (Cohen 1988; Field, 2009). It is the probability that the null hypothesis (H_0) will be rejected when it is actually false. As the probability of failing to reject a false hypothesis is β, then power equals 1-β (Howell, 2010). An acceptable recommendation is to utilize the power level of 0.8 as suggested by Cohen (1988). This implies that there is an 80% chance of detecting an effect if one genuinely exists.

The significance level of a study is the probability that the null hypothesis will be rejected when it is actually true. It is a probability level of the risk that there is a difference whereas no difference exists. A common setting is 0.05, or 5%, which means that 5 out of 100 times, an extremely low probability value will actually be observed if the null hypothesis is true (Creswell, 2012).

The following input parameters were therefore specified in this study: effect size (f^2) was set to 0.2, significance level (α) was set at 0.05, while the statistical power level (1-β) was set at 0.8. With seven latent variables and 23 observed variables, the online sample size calculator by Soper (2019) yielded a minimum sample size of 425 persons. When the five moderating variables are included in the calculation (making a total of 12 latent variables and 23 observed variables), the minimum sample size is 500 persons. Although both minimum sample size values are in line with the suggestion of 300 or more persons (Hair et al., 2015; Little, 2013), the higher value of 500 was selected for this study. The higher value selected also helped to offset any problems with missing data, as suggested by Hair et al. (2015).

Data Collection and Survey Procedure

The different methods of data collection for a survey instrument include mail, telephone, the Internet, personal interview, or group administration (Fowler, 2014). The use of the Internet for data collection for surveys involves a choice among three methods: via email only, via a website, or via a web link in an email sent to respondents (Babbie, 2013). Data collection through the Internet has become common, as a survey can be easily created by anyone who has access to online survey software such as Survey Monkey, Zoomerang, or Instant Survey (Sue & Ritter, 2012).

The current study utilized the Internet as the data collection method using a questionnaire as the instrument. The questionnaire was developed using Google Forms ® and presented electronically to participants via a uniform resource locator (URL) link on the MTurk hosting platform. Electronic data collection through the Internet provides the researcher with an easy and quick form of data collection (Creswell, 2012). Other advantages of the use of a website link to complete a survey include anonymity of participants, the ability to obtain sensitive data, the low unit cost of data collection, and provides time for thoughtful answers by respondents (Fowler, 2014; Sue & Ritter, 2012).

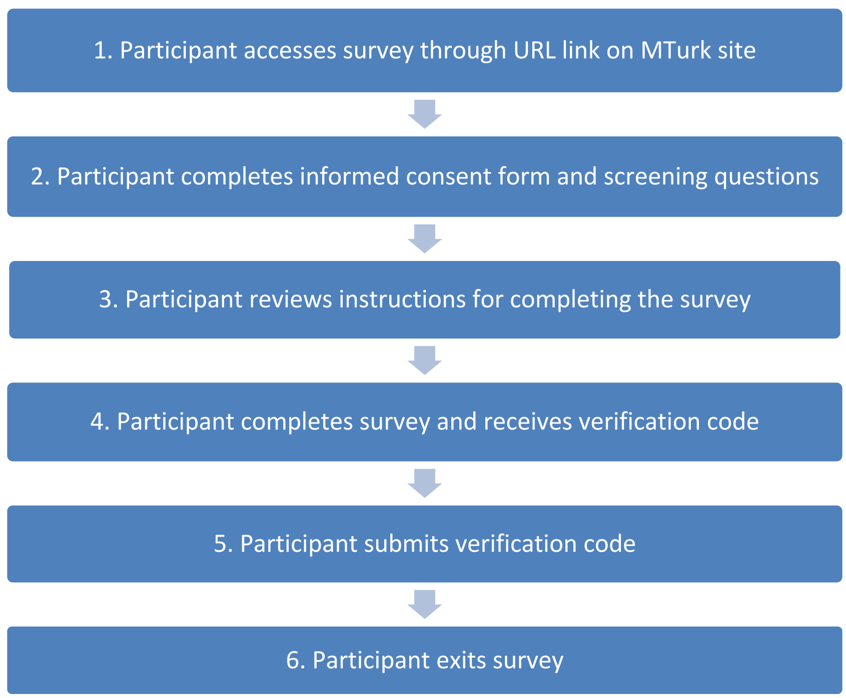
There are also some potential disadvantages using the Internet for data collection. Sue and Ritter (2012) noted that it could take a longer time to obtain the desired sample size and that respondents could abandon the survey at any time. The use of MTurk with the available payment incentive ensured that the required number of respondents was attained within a reasonable time. To minimize the risk of respondents quitting, questions were as short as possible, and the questionnaire was pretested with a small set of persons to assess the face and content validity. Any feedback received from the pretest was used to improve the questionnaire prior to the full-scale deployment. The use of a payment incentive should also help prevent the abandonment of the survey (Sue & Ritter, 2012). Another potential disadvantage is related to the restriction of the sample to Internet users only. Although the restriction could be a potential limitation of the study, as previously mentioned in the earlier section, the MTurk sample is considered to be somewhat representative of the U.S. population as a whole.

Per the policy of Embry Riddle Aeronautical University (ERAU), all forms of research involving human participants require assessment and approval by the Institutional Review Board (IRB) for the protection of human subjects in research, before the research is initiated. Thus, all materials for the survey, including the informed consent form, questionnaire, and the detailed procedures, were sent by email to the IRB for approval prior to the commencement of the study.

Following the receipt of approval from the IRB, the study was posted on the MTurk website. Intended participants were able to read an introduction about the survey, and if interested, were required to click on a URL link that directed them to the survey. Upon access to the survey, the participants were first presented with an informed consent form and two screening questions before access to the remainder of the survey. They were also provided with instructions for completing the questionnaire and were reminded that they could choose to discontinue the questionnaire at any time. The questionnaire contains options based on the variables in the study; participants were, therefore, required to select their responses to the independent (exogenous) variables and the dependent (endogenous) variable on 5-point Likert-type scales. It is expected that a participant could complete the questionnaire within 10 minutes. The detailed process followed by a participant to complete the study is shown in Figure 4.

Figure 4

Process Flow for Participants



After completing the questionnaire, participants were required to enter a verification code which enabled them to receive a reward from the MTurk system. The reward for participants who successfully completed the questionnaire and submitted the verification code was $0.50. The data collection process continued until at least 500 usable responses were attained.

Research Instrument

The research instrument for this study was an electronic questionnaire. The questionnaire used measurement items that were derived from existing items in previous studies, with minor modifications that reflected the context of this study. The sources of the measurement items were presented in Table 5. The questionnaire is presented in Appendix B, while the full details of the variables and statements used in the questionnaire are shown in Appendix C.

The first section of the questionnaire provides a general introduction to the study and includes an informed consent form. It includes answers to the most common questions participants may have regarding aspects of the study such as privacy and confidentiality. It also contains the contact details of the researcher in case participants require further information. The informed consent form is a request for participants to confirm their willingness to participate in the study by responding to a question in the form of a radio button choice of either ‘Yes’ or ‘No’. This is a mandatory question, and participants can only proceed with the survey by answering ‘Yes’ which indicates their informed consent has been provided.

The informed consent form was followed by two ‘Yes’ or ‘No’ questions designed to confirm participants’ eligibility prior to proceeding with the survey. The two questions are (1) *Are you currently registered as an MTurk worker in the United States?* and (2) *Are you 18 years of age or older?* Participants are considered eligible if they answered ‘Yes’ to both questions.

Participants were then presented with some information about biometric systems and the following scenario that was used to answer the questions in the next section:

"You have arrived at your local airport for a scheduled flight between two major cities. Upon approaching the check-in area, you are advised that there is an option to complete your entire check-in, baggage drop and aircraft boarding using only facial recognition as the means of identification and verification for the flight." The section contains questions used to assess the factors postulated to influence passengers' intentions to use biometric technologies at airports. The factors (constructs) used are attitudes, subjective norms, perceived behavioral control, perceived ease of use, perceived usefulness, and intention to use. Privacy is also included as a predictor and as a moderating factor to intentions to use biometrics. These constructs feature a five-point, Likert-type bipolar scale with endpoints and scores ranging from ''strongly disagree'' (-2) to ''strongly agree'' (+2). Each construct was evaluated by a minimum of three question items, as suggested by Hair et al. (2015). Participants were also allowed to state any additional comments they could have on the use of biometric systems.

The next section sought participants' demographic information in terms of age (in years), gender (male or female), and highest education level attained (high school, bachelor's, master's, or doctorate). Other demographic information that was requested included ethnicity and annual total income of respondents. Participants were also required to signify their past use of facial recognition technology at an airport. The demographic information collected was used to present characteristics of the research participants and allowed a comparison of the participants to the general population for generalization purposes (Salkind, 2010).

Clason and Dormody (1994) described individual single question items as Likert-type items, while the combined composite score of four or more Likert-type items was referred to as a Likert scale. They also noted that the use of Likert scale data from respondents assumes that the latent variables are continuous, and that the value represents the respondents' attitudes and opinions (Clason & Dormody, 1994). Multiple statements from each construct were thus combined into a single composite score (the average) per construct during the data analysis process, assuming the Cronbach's Alpha of these statements is high. Although Likert scales are ordinal data, there is support for their use as continuous variables and their analysis as interval data (Boone & Boone, 2012; Carifio & Perla, 2007, 2008; Willits, Theodori, & Luloff, 2016; Zumbo & Zimmerman, 1993). The analysis of Likert scale data responses by parametric methods was also found to yield reliable results even when some statistical assumptions were violated (Norman, 2010; Sullivan & Artino, Jr., 2013).

The construct *attitudes* was measured by four question items (AT1, AT2, AT3, AT4), adapted from scales by Chen et al. (2007) and Taylor and Todd (1995). Subjective norms was measured by three question items (SN1, SN2, SN3), adapted from scales by Chen et al. (2007), Reza Jalilvand and Samiei (2012), and Taylor and Todd (1995). The measurement scale for *perceived behavioral control* used three question items (PB1, PB2, PB3) and was adapted from Taylor and Todd (1995). The construct *perceived ease of use* was measured by four question items (PE1, PE2, PE3, PE4), while *perceived usefulness* was measured by three question items (PU1, PU2, PU3); both using scales adapted from Lu, Chou, and Ling (2009) and Wang et al. (2003). *Privacy* was measured by three question items (PR1, PR2, PR3) adapted from scales by Albashrawi and Motiwalla (2017) and Hong and Thong (2013). Finally, *intention to use* was measured by three question items (IN1, IN2, IN3) and with scales adapted from Al Ziadat (2015), Lu et al. (2009), and Wang et al. (2003).

The final section of the survey contains instructions for participants to exit the survey and receive their rewards. Participants were required to enter a verification code which they could then use to receive the reward from the MTurk system. The entire survey process could be completed within 10 minutes.

Pilot Study. A pilot study of a research instrument involves the completion and evaluation of the instrument by a small number of individuals (Creswell, 2012). The purpose of the pilot study is to test the instrument (the questionnaire) prior to the full-scale study to minimize the likelihood of participants having problems with the questionnaire. The pilot study also allows some assessment of the validity and the reliability of the questionnaire (Saunders et al., 2009).

For this research, two pilot studies were conducted using samples of at least 100 persons from MTurk for each study. Using these samples ensured that the pilot study samples were as similar as possible to the target population (Salkind, 2010; Van Teijlingen & Hundley, 2002). The second pilot study was conducted following the analysis of the data from the first study that showed reliability and validity concerns with a portion of the instrument. Participants in both pilot studies were able to provide written comments regarding issues with the questionnaire such as the content, clarity of instructions, ambiguous wording of questions, or the time taken to complete the survey. The feedback from the participants in the pilot studies was also used to make changes to improve the questionnaire before it was deployed for the main study. Any improvements made to the questionnaire were reported in detail. To avoid contamination problems, the participants from the pilot studies were excluded from participation in the main study, and any data gathered from the pilot studies were not considered in the results of the main study.

Instrument Reliability. The reliability of an instrument measures the stability and consistency of the scores over repeated observations and at different times (Babbie, 2013; Creswell, 2012). Reliability is best checked during the stage of wording the questions and at the time of a pilot study, and the instrument is considered to be reliable if it produces similar results under constant conditions on all occasions (Bell, 2005). Drost (2011) advised that the reliability of an instrument can be enhanced by writing items more clearly, ensuring test instructions can be understood without difficulty, and having clear rules for the scoring of the measurement items.

The process to assure the reliability of this study involved three steps. First, it was important to check that the instructions provided to participants to aid in the completion of the survey as well as the questions on the survey were clear and unambiguous. Babbie (2013) also noted that participants should only be asked about things that are relevant to them and things that they are likely to know the answer to. The second measure that was used to improve reliability involves assessing underlying constructs with the use of multiple question items. Since the separate items of the scale are all required to measure the same construct, they should, therefore, all be highly intercorrelated (Hair et al., 2015). There were at least three questions for each construct in this study. Finally, the pilot studies were conducted, and a reliability coefficient, which evaluates the whole scale, was computed using IBM SPSS™ statistical software. Cronbach's Alpha (α) is a popularly used measure with a widely agreed upon lower limit of .70 (Hair et al., 2015).

Any items with α lower than .70 from the pilot studies were revised or removed from the scales.

Instrument Validity. In addition to reliability, the measurement instrument must also be checked for validity. The validity of a measurement instrument is the extent to which the instrument adequately reflects the actual meaning of the concept under consideration (Babbie, 2013). Measuring the extent of validity of an item or instrument will enable a researcher to determine whether the item or instrument accurately measures or describes what it is supposed to measure or describe (Bell, 2005). This study assessed two types of validity – face validity and construct validity.

Face validity assesses the individual items and concept. Face validity is considered adequate when the measured items are conceptually consistent with the definition of the construct (Hair et al., 2015). Although face validity is a subjective assessment and could be considered a weak form of validity (Drost, 2011), Hair et al. (2015) noted that face validity must be clarified before theoretical tests are conducted, when using confirmatory factor analysis (CFA). As this study utilized CFA, face validity was ensured through the pilot studies and feedback from expert reviewers selected for their experience in research.

Construct validity refers to the extent to which measured variables actually depict the theoretical latent construct they intend to measure (Hair et al., 2015). The test for construct validity in the current study involved two measures: convergent validity and discriminant validity. The two measures are described in the section on data treatment. The measurement instrument was only considered to be reliable and valid when the reliability, convergent validity, and discriminant validity of the factor structure were confirmed.

Ethical Considerations

All processes involved in research from the design to the writing of the report must be completed with ethical considerations in mind. While members of a group normally agree on the tenets of ethical principles among themselves (Babbie, 2013), a basic requirement for the use of a survey instrument in research is that no individual should suffer any form of consequence from participating in the survey (Fowler, 2014). Ethical considerations were addressed in this study through the following methods: informed consent, anonymity and confidentiality, analysis and reporting, and by the IRB.

Informed Consent. The concept of informed consent considers the voluntary participation and the protection of participants from any form of harm at all times during the study. Informed consent requires that all participants acknowledge that their voluntary participation assumes that they fully understand any possible risks that could be involved in the study (Babbie, 2013). In this present study, the introduction section at the beginning of the questionnaire detailed the purpose of the research and a description of the study. Participants were able to confirm if they wanted to take part in the study through an informed consent form at the end of the section. In terms of protection from possible psychological harm, the questions have been carefully designed, and participants were able to decline to answer any question that could make them feel uncomfortable. Participants were also able to choose to withdraw from the survey at any time during the study.

Anonymity and Confidentiality. A research study is anonymous when there is no way for researchers or readers to identify participants by their responses to the questions in the study (Babbie, 2013; Bell, 2005). With confidentiality, a researcher promises that participants will not be identified or presented in an identifiable form, even when it could be possible to identify participants (Babbie, 2013; Bell, 2005). To assure anonymity, this study did not require participants to disclose any personally identifiable characteristic. Only general demographic information was requested, and there is no way to identify any participant from the information. All data that was collected as part of this study was treated as confidential data. Identification numbers were used to represent participants, while the computer systems used to store data were password protected.

Analysis and Reporting. Ethical considerations in respect to the analysis and reporting of data in a research study are related to researchers' obligations to the research community. The researcher has an obligation to report the results in full, including any shortcomings, limitations, or negative findings that may occur from the analysis of the study (Babbie, 2013). This study was conducted in an open manner, and any pitfalls or problems experienced were reported, as suggested by Babbie (2013).

Institutional Review Board (IRB). An IRB reviews all research proposals prior to the initiation of the research to safeguard the rights and welfare of human subjects during the study (Babbie, 2013). While the IRBs greatest concerns appear to be focused on ensuring that the possibility of any harm or discomfort to participants is minimal, the IRB review process also helps to protect researchers and institutions (Fowler, 2014). As this study involved human subjects, the procedures and research followed the guidelines of the IRB of Embry Riddle Aeronautical University (ERAU). An application for approval of the research was submitted to the IRB, and the data collection process did not start until IRB approval was obtained. A copy of the IRB approval to conduct the research is presented in Appendix A.

Data Analysis

The current study utilized structural equation modeling (SEM) as the data analysis method. The use of SEM involves not only a single process but a family of statistical tools that are used to examine the structure of the interrelationships among multiple variables (Hair et al., 2015). SEM is considered flexible, has the ability to differentiate between observed and unobserved (latent) variables, and is applicable to both experimental and non-experimental data (Kline, 2011). SEM is also a commonly adopted approach to investigate the relationships between latent constructs indicated by multiple measures defining a research model (Singh & Sharma, 2016; Westland, 2010). This study has seven latent constructs: attitudes, subjective norms, perceived behavioral control, privacy, perceived ease of use, and perceived usefulness are classified as independent variables. The seventh construct, intention to use, is classed as the dependent variable. SEM is thus considered to be an appropriate data analysis technique, since the major factors in this study are latent variables.

Another reason for selecting SEM as the statistical tool is due to its ability to handle structural and complex models (Nachtigall, Kroehne, Funke, & Steyer, 2003). The research theoretical framework for this study contains a TPB model in which multiple hypothesized relationships were analyzed simultaneously. The literature review from the previous chapter also highlighted several studies that used SEM to examine behavioral intentions (Bentler & Speckart, 1981; Chou & Ling, 2009; Liao et al., 2007; Lu et al., 2009; Ryu et al., 2003). Since the purpose of this study was to determine the degree to which the constructs influence passengers' use of biometric systems, SEM was considered a suitable method for the analysis.

SEM, like all statistical analysis measures, has several underlying assumptions that are required to enable reliable conclusions to be made. Byrne (2016) noted that from the early SEM analyses completed, the data used must have multivariate normal distribution and must be of a continuous scale. Other standard SEM assumptions include completely random missing data, sufficiently large sample size, independence of scores, and correct model specification (Kaplan, 2009; Kline, 2011). Finally, there should be no outliers, and exogenous variables are measured without error (score reliabilities all equal 1.00).

Nonnormality of the data was addressed through transformations. For missing data, Hair et al. (2015) suggest the following possible options: imputation, approaches that are model-based, and deletion (either pairwise or listwise). They also advise that any of the options would be appropriate if missing data are random, less than 10 percent of observations, and the factor loadings are relatively high (0.7 or greater). The final sample size of 689 participants was more than the specified minimum sample size of 500 persons, to help offset missing data problems. The specification of the model is also described in detail, and any outliers were deleted from further analysis (Hair et al., 2015).

While there have been current efforts focused on the development of estimators to be used with nonnormal and categorical or ordinal data (Byrne, 2016; Kaplan, 2009), this study tested the assumptions and subsequently utilized maximum likelihood estimation

(MLE) as the SEM estimation procedure. Data analysis in this study was conducted using IBM® SPSS® Statistics and AMOS in three steps: descriptive statistics, CFA, and SEM.

Descriptive Statistics. Descriptive statistics are normally used to present the detailed features of a sample or the relationship among variables in a sample and summarize the results in a manageable form (Babbie, 2013). The descriptive statistics presented in this current study include frequency, count, mean, and standard deviation for the demographic information and other variables and constructs, as may be applicable. The presentation was done using numbers, tables, graphs, and by general discussion in the results and discussion sections of the study. The initial examination of the characteristics of the data also included a check to identify any missing values in the data.

While descriptive statistics are considered useful, they only provide a summary of the observations. As this study was intended to generalize from the sample to the population, further strategies in the form of inferential statistics were required to assess the reliability of the generalization (Peck, Olsen, & Devote, 2012). This requirement thus led to the next stage of the data analysis process.

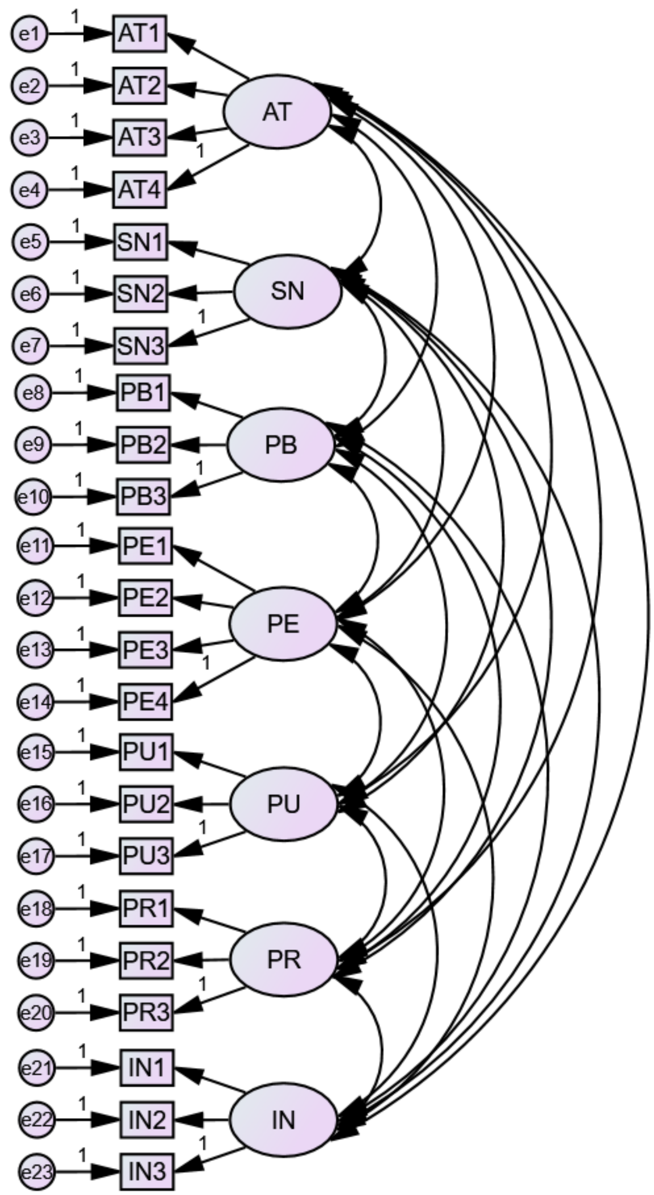
Confirmatory Factor Analysis (CFA). The CFA is a type of SEM that involves the analysis of measurement models (i.e., the relationships between observed measures and latent variables; Brown, 2006). Byrne (2016) noted that a CFA is appropriate to be used when (a) there is some understanding of the basic latent variable arrangement, (b) relationships between the observed measures and latent factors can be postulated, and (c) the proposed framework can be tested statistically. For this study, the review of the literature presented in the previous chapter identified factors that could influence passengers’ intentions to use biometric technologies. The literature review also provided support for the use of the TPB as a theoretical framework for the study. Thus, CFA was used to present a confirmatory test of the measurement theory and to provide a validation of the measurement model. This includes examining the latent structure of the instrument and validating the theoretical constructs (Brown, 2006).

The CFA model was developed using the IBM® SPSS® AMOS software. The assumption of normality was checked based on the values of skewness and kurtosis. As noted by Singh and Sharma (2016), endogenous variables normality is acceptable if the absolute values of skewness and kurtosis are between +2 and −2. Byrne (2016), however, noted that kurtosis is more of a concern in SEM and suggested that values of kurtosis equal to or greater than 7 are suggestive of nonnormality. Nonnormality of the data due to skewness or kurtosis was addressed through transformations (Kline, 2011). The assessment of normality of the data can also be considered from the presence of outliers (Byrne, 2016). Any outliers were detected from AMOS using the observations farthest from the centroid, also known as Mahalanobis distance (d2). Observations adjudged to be outliers were deleted from further analyses.

The initial hypothesized CFA model presented in Figure 5 shows the seven latent variables and their corresponding observed variables: AT (attitudes), SN (subjective norms), PB (perceived behavioral control), PE (perceived ease of use), PU (perceived usefulness), PR (privacy), and IN (intention to use). The model hypothesizes that all seven latent variables (constructs) are intercorrelated, each observed variable loads on only one factor, and error terms associated with each observed variable are uncorrelated.

Figure 5

Hypothesized CFA Model for the Study



The CFA model was then evaluated using Goodness-of-fit (GOF) indices. The GOF indices that were used in this study include Comparative fit Index (CFI), Goodness of fit Index (GFI), and the Adjusted Goodness of fit Index (AGFI). Others are Normed Fit Index (NFI), Root Mean Square Error of Approximation (RMSEA), and Normed Chi-Square ($\chi2$ /df). The recommended values for acceptable fit for the GOF indices are presented in Table 6. Values of the calculated indices were checked against the standard values to check for a satisfactory measurement model fit.

Table 6

Recommended Standard Values for Goodness of Fit Indices

Indices	Recommended values	References
CFI	≥ 0.95	Kline (2011); Singh and Sharma (2016)
GFI	≥ 0.90	Hair et al. (2015); Singh and Sharma (2016)
AGFI	≥ 0.90	Singh and Sharma (2016)
NFI	≥ 0.90	Singh and Sharma (2016)
RMSEA	≤ 0.05	Byrne (2016); Hair et al. (2015)
Normed Chi-Square ($\chi2$ /df	$1<\chi2/df<3$	Singh and Sharma (2016)

In addition to these, two predictive fit indices, the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) were also reported from AMOS. These assess model fit by comparing two or more models, with the smaller values representing a better fit of the hypothesized model (Byrne, 2016; Kline, 2011).

Where the values for the CFA model showed an unacceptable model fit, post-hoc analysis was conducted to re-specify and re-estimate the model (Byrne, 2016). This included an examination of modification indices (MI) which show the extent to which the model is appropriately described (Byrne, 2016). Specifically, MIs were checked for correlating error terms with high values and question items with poor factor loadings. As noted by Hair et al. (2015), any changes suggested by a modification index was only done if justified by theory. Only a single change was made to the model each time, while each change was followed by re-specification and re-estimation of the model to check for adequate fit.

After a satisfactory measurement model fit was obtained, the construct validity was assessed using convergent validity and discriminant validity. Convergent validity checks if items that are indicators of a specific construct converge or share a high proportion of variance in common. It was measured using average variance extracted (AVE), with an AVE of 0.5 or higher suggesting adequate convergence (Hair et al., 2015). Discriminant validity is the extent to which a construct is distinct from other constructs. It was measured by comparing the AVE values for any two constructs with the square of the correlation estimates between the two constructs. Greater AVE values suggest that discriminant validity is supported (Hair et al., 2015).

The formula to calculate AVE as stated by Hair et al. (2015) is presented in equation 2.

$$\text{AVE} = \frac{\sum_{i=1}^{n} L_i^2}{n}, \tag{2}$$

where:

L_i = standardized factor loading.

i = the number of items.

n = n items.

Reliability was also assessed as a measure of convergent validity (Hair et al., 2015). This was done using a construct reliability (CR) index. A CR index of .70 or higher is suggestive of good reliability (Hair et al., 2015). The equation used to compute the CR value as stated by Hair et al. (2015) is presented in equation 3.

$$CR = \frac{(\sum_{i=1}^{n} \lambda_i)^2}{(\sum_{i=1}^{n} \lambda_i)^2 + (\sum_{i=1}^{n} \delta_i)} \qquad (3)$$

where:

λ_i = standardized factor loading.

i = the number of items.

n = *n* items.

δ_i = error variance terms for a construct.

Once the convergent validity, discriminant validity, and reliability of the measurement model were confirmed as acceptable, the study proceeded to the next step of the data analysis.

Structural Equation Modeling (SEM). SEM techniques are used to test a structural model by the simultaneous estimation of multiple equations that include factor analysis, multiple regression analysis, and path model analysis (Singh & Sharma, 2016). The SEM model depicts relationships among latent variables only while the specification of the model will be based on the theory proposed by the research, and involved the identification of all relationships that are hypothesized to exist among the constructs (Byrne, 2016; Hair et al., 2015). This includes the direct relationships between independent and dependent variables and the indirect relationships between observed variables and unobserved latent variables, or constructs (Schreiber, 2008).

The testing of the SEM model followed the same process and used the same GOF indices as the CFA model to assess the structural model fit. This also included any post-hoc analysis that may be required. In addition to the GOF indices, the individual parameter estimates were examined to check: (a) statistical significance and predicted direction, and (b) non triviality using the completely standardized loading estimates. Since the goal of SEM is to provide a test of a theory, the SEM model was considered acceptable only when the model fit is acceptable and path estimates representing each hypothesis are significant and in the predicted direction. Compared to the CFA model that shows all constructs with noncausal relationships, the SEM model specifies the related constructs and the nature of each relationship. The main differences between the CFA model and the SEM model are summarized in Table 7.

Table 7

Differences Between CFA Model and SEM Model

Measurement model (CFA)	Structural model (SEM)
Emphasis is on the relationships between latent constructs and measured indicator variables	Emphasis is on the nature and magnitude of the relationships between constructs
Assumes each construct is related to each other construct	Specifies which constructs are related and the nature of each relationship
No distinction between exogenous and endogenous constructs	Exogenous constructs are distinguished from endogenous constructs
Relationships are presented as simple correlations with a two-headed curved arrow	Exogenous constructs have no arrows entering them while endogenous constructs are determined by other constructs shown by a pattern of single-headed arrows that point to endogenous constructs

Note. Adapted from Hair et al. (2015).

Following the confirmation of a satisfactory fit for the SEM model, the hypotheses testing was conducted using standardized regression weights (estimates), *t*-values, and significance level as reported via IBM ® SPSS ® AMOS. It was thus possible to examine the relationships hypothesized in the model.

Chapter Summary

The chapter presented a confirmation that the study followed a quantitative approach and a correlational design using a survey instrument to investigate the factors that influence passengers' intentions to use biometric technologies at airports. Following the conclusion of the questionnaire design and IRB process, opinions of a sample of persons from MTurk were sought regarding their intentions to use biometrics. The use of SEM for the analysis of the data ensured that the factors that contribute most to influencing passengers' intentions to use biometric technologies can be identified. The next chapter presents the findings from the study.

Chapter IV: Results

The present study examined the extent to which factors of the theory of planned behavior (TPB) and the additional factors of perceived ease of use and perceived usefulness influence passengers' intentions to use biometric technologies at airports. This chapter presents the results of the study. First, the results received from the face and content validity assessment are summarized. Next, the results and analysis from the pilot studies and the main study are presented following the methodology detailed in the previous chapter. Finally, the chapter concludes with a summary of the main results.

Face and Content Validity Assessment

The face and content validity were assessed by seven people. These included two people from the researcher's aviation Ph.D. program with knowledge of constructing surveys, one other Ph.D. holder, and two people with a combined experience of more than 20 years in the aviation industry. The other two people were frequent travelers with some awareness of biometric technologies. All the participants from the face and content validity check reported that they completed the survey within the expected 10 minutes duration. Some of the changes made to the questionnaire based on the reviewers' assessments include (a) inclusion of a question on participant's previous use of facial recognition technology, (b) addition of the option 'other' to the gender question, and (c) clarification on the categories used for the question on race. One other significant change was to amend the logic on Google Forms ® to ensure only participants that responded 'Yes' to the two screening questions could continue to complete the survey.

Pilot Studies

Two pilot studies were conducted before the main study. After completing the first pilot study, the analysis of the data showed that there were reliability and validity concerns with a portion of the instrument. The survey instrument was therefore adjusted after the first pilot study, following which the second pilot study was conducted using the adjusted instrument.

Pilot Study 1

The first pilot study was conducted with a sample from Amazon ® Mechanical Turk ® (MTurk). There were 101 responses to the questionnaire in the first pilot study. During the data examination and preparation process, one of the responses was discovered to have two questions unanswered. This case was excluded from the analysis. A further examination of responses appeared to indicate three cases with the same scores across all questions. The cases were, therefore, excluded from the analysis leaving 97 usable responses. The responses to the latent variables were also checked for any missing values in the data. The following variables were observed to have one value missing: AT2, PB2, PB3, and PE2. Following the recommendation by Hair et al. (2015), the missing values were replaced using known replacement values. The replacement values used were valid values from similar observations in the sample.

The demographic information of the respondents showed that there were 60.8% male and 39.2% female respondents. The age groups with the most respondents were ages 31-40 years (47.4%) and 41-50 years (28.9%). Most respondents had a maximum education of a bachelor's degree (55.7%), while the predominant ethnic group was 'White or Caucasian' (75.3%). An overwhelming majority of respondents (95.9%)

reported that they had no prior use of facial recognition technology at an airport, while the annual incomes reported showed that the ranges $10,001-$30,000 (29.9%) and $30,001-$50,000 (21.6%) were the most prominent. The complete demographic characteristics for the respondents from the first pilot study are shown in Table 8.

Table 8

Summary of Basic Demographic Characteristics – Pilot Study 1

Characteristics	Subgroup Categories	Frequency (*N* = 97)	Percentage
Age	<=30 years	12	12.4%
	31-40 years	46	47.4%
	41-50 years	28	28.9%
	51-60 years	10	10.3%
	>=61 years	1	1%
Gender	Male	59	60.8%
	Female	46	39.2%
Highest Level of Education	High school certificate	36	37.1%
	Bachelor's Degree	54	55.7%
	Master's Degree	5	5.2%
	Doctorate Degree	2	2.1%
Ethnicity	Asian or Asian American	9	9.3%
	Black or African American	8	8.2%
	Hispanic or Latino	3	3.1%
	Mixed Race	3	3.1%
	White or Caucasian	73	75.3%
		1*	1%
Annual Total Income (USD)	<=10,000	13	13.4%
	10,001-30,000	29	29.9%
	30,001-50,000	21	21.6%
	50,001-70,000	13	13.4%
	70,001-90,000	7	7.2%
	>=90,001	12	12.4%
		2*	2.1%
Previous use of facial recognition technology at airport	No	93	95.9%
	Yes, once	2	2.1%
	Yes, More than once	2	2.1%

Note. * Number of respondents who did not respond to the question.

Following the data preparation process, the CFA model was constructed and analyzed using IBM ® SPSS ® AMOS 24. The assumption of normality was checked using the values of skewness and kurtosis. From the AMOS output, the skewness and kurtosis values were between +2.238 and −1.257. This is comparable to the recommendation of Singh and Sharma (2016) that normality is acceptable provided the absolute values of skewness and kurtosis are within the range of +2 and −2. Furthermore, Byrne (2016) suggested that kurtosis values below 7 are indicative of data normality. Therefore, there was no need to transform the variables.

The presence of outliers was checked from the AMOS output using the observations farthest from the centroid, also known as Mahalanobis distance (D^2). Byrne (2016) noted that an outlier is an observation that has a D^2 value distinct from all other D^2 values. There was no case with a distinct D^2 value or a D^2 value above 100 that could represent the presence of an outlier; thus, no case was deleted.

The evaluation of model fit was conducted using the indices presented in Table 9. A comparison of the initial results against the standard values shows that the CFI and the Normed Chi-Square ($\chi 2$ /df) are the only indices that indicated acceptable model fit. All other indices had a poor model fit. The attempt to re-specify the model was performed by checking the modification indices (MIs) from the AMOS output. The highest meaningful MI value that could be considered was 13.259 (which was the path between e14 and e21, two error terms of separate constructs). However, Hair et al. (2015) advised that running CFA models with between-construct error covariances could question the construct validity of the construct. Furthermore, the estimated parameter change of -0.066 means that allowing the path between the two error terms to be estimated would not make a significant change to the model fit. It was therefore decided not to add a covariance between the two error terms. There was no other meaningful MI value that could be considered; therefore, there was no need to re-specify the model. Byrne (2016) also noted that MI values less than 10.00 are not likely to result in a significant change to the overall model fit.

Hair et al. (2015) suggested that overall model fit could be assessed using a combination of any of the absolute fit indices and any of the incremental fit indices. Therefore, the Normed Chi-Square ($\chi 2$ /df), an absolute fit index, and the CFI, an incremental fit index both indicated an acceptable model fit. Furthermore, because of the small sample size used in the pilot study, it was decided to proceed with the reliability and validity. The results of the fit indices for the first pilot study and the standard values are shown in Table 9.

Table 9

Model Fit Indices - Pilot Study 1

Indices	Standard Values	Results	Acceptable (Yes/No)
CFI	≥0.95	0.950	Yes
GFI	≥0.90	0.774	No
AGFI	≥0.90	0.702	No
NFI	≥0.90	0.885	No
RMSEA	≤0.05	0.083	No
Normed Chi-Square ($\chi 2$ /df)	$1<\chi 2/df<3$	1.654	Yes

Next, the reliability analysis was completed using the results from the AMOS output. The Construct Reliability (CR) was calculated with the aid of Microsoft Excel ® using the standardized regression weights (factor loadings) and the error variances. The results of the analysis are shown in Table 10.

The construct reliability of the perceived behavioral control (PBC) construct was the lowest of all constructs at .643 and below the reference figure of .7, while the

Cronbach's Alpha (α) at .495 was less than the lower limit of .70 suggested by Hair et al. (2015). The convergent validity, measured by the average variance extracted (AVE) was also lowest for this construct at .433, and less than the reference figure of .5 suggested by Hair et al. (2015). Therefore, the instrument did not demonstrate satisfactory reliability and convergent validity.

Table 10

Reliability Analysis and Validity - Pilot Study 1

Constructs	Item Questions	Factor Loadings (≥.5)	CR (≥.7)	α (≥.7)	AVE (≥.5)	MSV (<AVE)
Attitudes	AT1	.979	.957	.954	.847	.776
	AT2	.972				
	AT3	.925				
	AT4	.794				
Subjective Norms	SN1	.953	.979	.977	.940	.618
	SN2	.995				
	SN3	.960				
Perceived Behavioral Control	PB1	.920	.643*	.495*	.433*	.294
	PB2	.185*				
	PB3	.646				
Perceived Ease of Use	PE1	.828	.924	.922	.751	.294
	PE2	.893				
	PE3	.863				
	PE4	.882				
Perceived Usefulness	PU1	.913	.930	.928	.817	.514
	PU2	.925				
	PU3	.872				
Privacy	PR1	.975	.970	.969	.915	.482
	PR2	.959				
	PR3	.935				
Intention to Use	IN1	.962	.969	.969	.913	.776
	IN2	.962				
	IN3	.943				

Note. * Indicates unacceptable reliability or validity value.

Finally, Table 10 also shows the maximum shared variance (MSV) which is one of the measures to present the assessment of discriminant validity. All the MSV values are below the corresponding AVE values for all the constructs. The second measure to present the assessment of discriminant validity is shown in Table 11. The measure considers a pair of constructs and presents a comparison of the AVE with the correlation estimates. The square roots of the AVEs are all greater than the between-construct correlation estimates which indicates sufficient discriminant validity of the constructs.

Table 11

Discriminant Validity – Pilot Study 1

	PU	AT	SN	PB	PE	PR	IN
PU	0.904*						
AT	0.717	0.921*					
SN	0.564	0.786	0.970*				
PB	0.275	0.214	0.130	0.658*			
PE	0.361	0.284	0.193	0.542	0.867*		
PR	-0.371	-0.626	-0.524	-0.160	-0.180	0.956*	
IN	0.668	0.881	0.746	0.170	0.348	-0.694	0.956*

Note. * Indicates Square root of AVEs.

For the factor loadings, Hair et al. (2015) suggested that the minimum values should be .5 and preferably .7 or higher. The factor loading for the question item PB2 was .185. Since this construct has only three indicators, the question item was not removed but was rephrased and additional details included to make the question clearer. Thus, the item PB2 (“Using biometrics at airports is entirely within my control”) was changed to “The choice to use biometrics at airports is entirely up to me”. The second pilot study was therefore conducted to check the amended questionnaire.

Pilot Study 2

The second pilot study was also conducted using a sample from Amazon ® Mechanical Turk ® (MTurk) and yielded 102 responses. Data examination revealed four cases with similar scores across all questions. The cases were therefore excluded from the analysis leaving 98 usable responses. The check for missing values in the data showed that the variables PU1, AT1, and PE2 had one value missing while the variable IN3 had two values missing. The missing values were replaced with valid values from similar observations in the sample using known value replacement, as in Pilot Study 1.

The respondents from the second pilot study were 56.1% male and 43.9% female. Most of the respondents were between the ages of 31-40 years (34.7%), while 28.6% were less than 30 years. The education and ethnic group categories showed similar results to the first pilot study respondents - most respondents had a maximum of a bachelor’s degree (46.9%), while the predominant ethnic group was ‘White or Caucasian’ (77.6%). The annual incomes reported showed that the ranges $10,001-$30,000 (24.5%) and $30,001-$50,000 (30.6%) were the most prominent. Finally, an overwhelming majority of respondents (90.8%) reported that they had no prior use of facial recognition technology at an airport. The complete demographic characteristics for the second pilot study respondents are shown in Table 12.

The CFA model also followed the same process as with the first pilot study. There was no need to transform any of the variables and no need to delete any of the observations.

Table 12

Summary of Basic Demographic Characteristics – Pilot Study 2

Characteristics	Subgroup Categories	Frequency (*N* = 98)	Percentage
Age	<=30 years	28	28.6%
	31-40 years	34	34.7%
	41-50 years	18	18.4%
	51-60 years	13	13.3%
	>=61 years	5	5.1%
Gender	Male	55	56.1%
	Female	43	43.9%
Highest Level of Education	High school certificate	38	38.8%
	Bachelor's Degree	46	46.9%
	Master's Degree	12	12.2%
	Doctorate Degree	2	2.0%
Ethnicity	Asian or Asian American	9	9.2%
	Black or African American	5	5.1%
	Hispanic or Latino	4	4.1%
	Mixed Race	4	4.1%
	White or Caucasian	76	77.6%
Annual Total Income (USD)	<=10,000	7	7.1%
	10,001-30,000	24	24.5%
	30,001-50,000	30	30.6%
	50,001-70,000	15	15.3%
	70,001-90,000	9	9.2%
	>=90,001	11	11.2%
		2*	2.0%
Previous use of facial recognition technology at airport	No	89	90.8%
	Yes, once	4	4.1%
	Yes, More than once	5	5.1%

Note. * Number of respondents who did not respond to the question.

The results of the model fit indices for the second pilot study are presented in Table 13. A comparison of the initial results against the standard values shows that the Normed Chi-Square ($\chi2$ /df) is the only fit index that indicated acceptable model fit. The process to re-specify the model showed that the highest MI value was 15.483 (between e3 and e6). As noted in the first pilot study, it is not advisable to run CFA models with between-construct error covariances. In addition, the estimated parameter change of

-0.076 is not likely to make a significant change to the model fit. There were no other meaningful MI values that could be considered to re-specify the model.

While the values of the fit indices from the second pilot study did not meet the standard values as stated in Table 13, it was decided to proceed with the assessment of reliability and validity for the following reasons. First, the CFI value of 0.942 is very close to the stated standard value of 0.95. Hair et al. (2015) also suggested that a model with a CFI value above 0.90 is a well-fitting model, while Hu and Bentler (1999) considered a value above 0.90 as acceptable. Second, the RMSEA value of 0.086 could be considered an indication of a reasonable fit (Browne & Cudeck, 1993) and of a moderate fit (Hu & Bentler, 1999). Third, the fit indices GFI, AGFI, NFI, and RMSEA are known to be affected by sample size (Curran, Bollen, Chen, Paxton, & Kirby, 2003; Marsh, Balla, & McDonald, 1988; West, Taylor, & Wu, 2012). With the small sample size for the second pilot study (*n* = 98), it was therefore decided to proceed to determine the reliability and validity of the instrument.

The results of the fit indices for the second pilot study and the standard values are presented in Table 13, while the specified CFA model for the study is shown in Figure 6.

Table 13

Model Fit Indices - Pilot Study 2

Indices	Standard Values	Results	Acceptable (Yes/No)
CFI	≥0.95	0.942	No
GFI	≥0.90	0.768	No
AGFI	≥0.90	0.693	No
NFI	≥0.90	0.874	No
RMSEA	≤0.05	0.086	No
Normed Chi-Square ($\chi2$ /df)	$1<\chi2/df<3$	1.721	Yes

Next, the reliability analysis was completed using the results from the AMOS output. The Construct Reliability (CR) was calculated with the aid of Microsoft Excel ® using the standardized regression weights (factor loadings) and the error variances. Table 14 shows the results of the analysis.

Table 14

Reliability Analysis and Validity - Pilot Study 2

Constructs	Item Questions	Factor Loadings (≥.5)	CR (≥.7)	α (≥.7)	AVE (≥.5)	MSV (<AVE)
Attitudes	AT1	.948	.946	.942	.817	.736
	AT2	.956				
	AT3	.931				
	AT4	.766				
Subjective Norms	SN1	.892	.957	.956	.881	.506
	SN2	.947				
	SN3	.975				
Perceived Behavioral Control	PB1	.831	.807	.759	.594	.575
	PB2	.524				
	PB3	.903				
Perceived Ease of Use	PE1	.798	.926	.925	.759	.575
	PE2	.907				
	PE3	.877				
	PE4	.898				
Perceived Usefulness	PU1	.884	.899	.886	.747	.503
	PU2	.880				
	PU3	.828				
Privacy	PR1	.963	.969	.969	.912	.530
	PR2	.953				
	PR3	.949				
Intention to Use	IN1	.979	.971	.970	.918	.736
	IN2	.955				
	IN3	.940				

The factor loading for the question item PB2 improved from .185 to .524. The construct reliability of the PBC construct improved from .643 to .807, Cronbach's Alpha was also seen to improve from .495 to .759, and AVE improved from .433 to .594. All the values were above the stated reference values. The construct reliability and the

Cronbach's Alpha figures for the other constructs were still higher than the reference value of 0.7, while the AVE figures also remained above the reference value of 0.5. To assess the discriminant validity, the MSV values for all constructs in Table 14 are seen to be lower when compared to the corresponding AVE values, while Table 15 shows that the square roots of the AVEs are all higher than the inter-construct correlations. These metrics indicate sufficient discriminant validity of the constructs.

Table 15

Discriminant Validity – Pilot Study 2

	PU	AT	SN	PB	PE	PR	IN
PU	0.864*						
AT	0.709	0.904*					
SN	0.405	0.625	0.939*				
PB	0.375	0.312	0.230	0.770*			
PE	0.499	0.381	0.292	0.758	0.871*		
PR	-0.422	-0.728	-0.513	-0.285	-0.298	0.955*	
IN	0.577	0.858	0.711	0.249	0.382	-0.669	0.958*

Note. * Indicates Square root of AVEs.

The revised instrument therefore demonstrated acceptable reliability and construct validity (as assessed using convergent validity and discriminant validity).

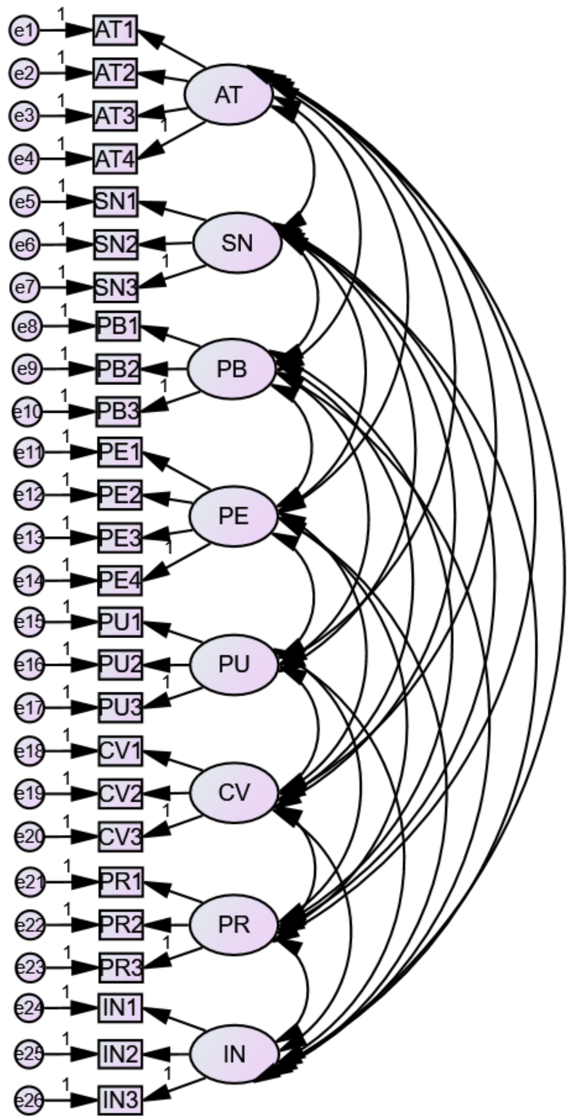
Coronavirus (COVID-19) Variable

COVID-19 is the name given to a new infectious disease by the World Health Organization. By the time the second pilot study was conducted, the disease had become a pandemic affecting many countries worldwide. Although the pandemic is a one-off event, the coronavirus variable was included as a control variable to help account for any influence on passengers' behavioral intentions to use biometric technologies at airports.

The coronavirus variable was defined in this study as a passenger's perception of the threat of the impact of the coronavirus (COVID-19) crisis on the use of biometrics. The survey instrument was therefore modified to include a Perceived Coronavirus Threat Scale developed by Conway, Woodard, and Zubrod (2020), while the COVID-19 variable was measured by three question items (CV1, CV2, CV3). An additional open-ended question was included for participants to respond on the perceived effect of the coronavirus on their behavioral intentions. The specified CFA model for the main study is presented in Figure 6 and shows the COVID-19 variable (CV) covaried with the other variables.

Figure 6

Specified CFA Model for the Main Study



Note. AT = Attitudes; SN = Subjective Norms; PB = Perceived Behavioral Control; PE = Perceived Ease of Use; PU Perceived Usefulness; CV = Coronavirus (COVID-19); PR = Privacy Concerns; IN = Intention to Use.

Main Study

Although the minimum sample size was earlier determined to be 500 persons, 700 responses were requested from Amazon ® Mechanical Turk ® (MTurk) for the main study. Following the publication of the survey on MTurk, only 23 responses were received within 72 hours. A closer examination of the parameters set for the survey on MTurk revealed that the worker requirements were inadvertently set to require only workers that were 'Masters' to complete the survey.

Peer, Vosgerau, and Acquisti (2014) noted that restricting the survey to only workers that were 'Masters' would reduce the size of the available population and increase the time to attain the required sample size. Furthermore, the additional qualifications requested from workers (HIT approval rate greater than 98% and more than 100 HITs approved) were considered sufficient to assure reliable and high quality responses (Peer et al., 2014).

The 'Masters' requirement was therefore removed, and the existing task containing the survey was cancelled. The survey with the revised requirements was subsequently re-published as a new task on MTurk. The change in the requirement expanded the available sampling frame and resulted in 757 responses in less than 24 hours. The additional responses beyond the requested 700 participants were likely due to workers that had accepted the previous task but had not submitted before it was cancelled.

The researcher received feedback from some participants. Two participants sent messages to the author through MTurk that they inserted the wrong codes after they had completed the survey. The author provided responses to the participants, assuring them that they will receive their compensation since they had completed the survey. Three other participants advised the author that they were unable to complete the survey and that the published time of 10 minutes was too short. The author advised them that all data completed prior to submitting the questionnaire will be removed and destroyed and will not be used for any analysis.

Summary of Initial Data Screening. The survey responses were downloaded to Microsoft Excel ® for initial data screening before being exported to SPSS for data analysis. During the initial data screening, it was discovered that eight respondents did not provide answers to two or more of the Likert scale questions. These cases were removed from the data. Further data examination revealed 60 cases where respondents provided similar answers across all Likert scale questions which could indicate that the respondents were unengaged during the study. The 60 cases were also removed from further analysis, resulting in 689 usable cases for the analysis, more than the minimum of 500 responses. The 689 cases from the total sample of 757 responses represent a completion rate of 91%.

The final screening measure checked for any missing values in the responses to the latent variables and found 33 missing values across different variables. The missing values were replaced with valid values from similar observations in the sample. The next section presents an analysis of the demographics of the study.

Demographics. The demographic data collected during the study included participants' age, gender, ethnicity, and highest education level attained. Participants were also asked to state their annual income in United States Dollars (USD) and to indicate if they had any prior use of facial recognition technology for the purpose of identification and verification at an airport. In addition, respondents were requested to signify whether the COVID-19 pandemic had any effect on their intentions to use biometrics. The demographic questions were not mandatory, so participants could choose to decline to answer any or all of the demographic questions. The complete demographic characteristics for the main study respondents are presented in Table 16.

Age. The majority of the respondents were within the two age groups of less than or equal to 29 years (26.6%) and 30-39 years (38.0%). Other age groups were represented as follows: 40-49 years (17.3%), 50-59 years (9.9%), and more than or equal to 60 years (8.3%). From the records reported by the U.S. Census Bureau (2019a), the population figures for the same age groups were less than or equal to 29 years (38.9%), 30-39 years (13.4%), 40-49 years (12.3%), 50-59 years (12.8%), and more than or equal to 60 years (22.7%). Although the U.S. population had a higher percentage of people less than 29 years (38.9%) compared to the survey respondents (26.6%), the percentage of respondents aged 60 years or older was significantly lower amongst the survey respondents, 8.3% compared to 22.7% for the national population. Furthermore, the median age for the survey respondents was 35 years compared to 38.3 years for the U.S. population. Overall, the respondents from the survey were, therefore, younger when compared to the national population. Prior studies (Berinsky et al., 2012; Heen, Lieberman, & Miethe, 2014; Huff & Tingley, 2015) have also found MTurk survey respondents to be younger than the national population.

Table 16

Summary of Demographic Characteristics – Main Study

Characteristics	Subgroup Categories	Frequency (*N* = 689)	Percentage**
Age	<=29 years	183	26.6%
	30-39 years	262	38.0%
	40-49 years	119	17.3%
	50-59 years	68	9.9%
	>=60 years	57	8.3%
Gender	Male	402	58.3%
	Female	284	41.2%
		3*	0.4%
Highest Level of Education	High school certificate	161	23.4%
	Bachelor's Degree	363	52.7%
	Master's Degree	143	20.8%
	Doctorate Degree	20	2.9%
		2*	0.3%
Ethnicity	American Indian or Alaska Native	2	0.3%
	Asian or Asian American	58	8.4%
	Black or African American	49	7.1%
	Hispanic or Latino	30	4.4%
	Mixed Race	19	2.8%
	Native Hawaiian or other Pacific Islander	1	0.1%
	White or Caucasian	529	76.8%
		1*	0.1%
Annual Total Income (USD)	<=9,999	26	3.8%
	10,000-19,999	49	7.1%
	20,000-34,999	111	16.1%
	35,000-49,999	113	16.4%
	50,001-74,999	187	27.1%
	>=75,000	177	25.7%
		26*	3.8%
Previous use of facial recognition technology at airport	No	550	79.8%
	Yes, once only	67	9.7%
	Yes, more than once	70	10.2%
		2*	0.3%
Any effect of COVID-19 crisis on perception of intention to use biometrics at airports?	Yes	131	19.0%
	No	558	81.0%

Note. *Number of respondents who did not respond to question.

** Percentages may not sum up to 100% due to rounding.

Gender. Results showed that there were more males (58.3%) than females (41.2%) among the respondents. This ratio of males to females among the respondents is different from the ratio among the U.S. population of 49% male and 51% female (U.S. Census Bureau, 2019a). A study by Garrow, Chen, Ilbeigi, and Lurkin (2020) found the gender split among MTurk respondents in the U.S. to be approximately 50% male and 50% female, which is closer to the overall U.S. population ratio. Prior research has found that the gender distribution of MTurk workers is at least as representative of the general U.S. population as other traditional subject pools (Berinsky et al., 2012; Paolacci et al., 2010). Researchers have also noted differences in demographics and behaviors between MTurk workers and the U.S. population (Arditte, Çek, Shaw, & Timpano, 2016; Mason & Suri, 2012; Paolacci & Chandler, 2014).

The noticeable difference in the male to female respondent ratio in the current study could be attributed to the cross-sectional approach adopted by the study. Furthermore, the ratio can also be compared to the study of demographics and dynamics of MTurk workers by Difallah, Filatova, and Ipeirotis (2018), who provide ongoing demographic characteristics of MTurk workers via their website. Their data for the period of this present survey showed that the gender ratio of MTurk workers available at the time was 55% male and 45% female (Difallah, Filatova, & Ipeirotis, 2020).

Highest Level of Education. More than half of the respondents (52.7%) stated that a bachelor’s degree was the highest level of education they had attained. This was followed by the high school certificate (23.4%) and a master’s degree (20.8%), while only 2.9% of respondents had obtained a doctorate degree. Data for the U.S. population showed that the combined categories of those with some college or associate degree and those with bachelor's degree were 46.7% of the population, while the combined categories of those with high school and less than high school graduate were 41.8% of the population. Those with advanced degrees were 11.4% of the population (U.S. Census Bureau, 2019a). The MTurk survey respondents thus had a level of education that was slightly higher than the U.S. population.

Ethnicity. In terms of the ethnic composition of the MTurk survey respondents, the majority (76.8%) belonged to the 'White or Caucasian' group. Data for the other groups were Asian or Asian American (8.4%), Black or African American (7.1%), Hispanic or Latino (4.4%), Mixed Race (2.8%), American Indian or Alaska Native (0.3%), and Native Hawaiian or other Pacific Islander (0.1%). Per the U.S. Census Bureau (2020), the composition of the MTurk respondents is also similar to the U.S. population in that the majority belongs to the 'White or Caucasian group', whether the grouping is considered as White alone (76.5%), or 'White alone, not Hispanic or Latino' (60.4%). Data for the other groups are as follows: Hispanic or Latino (18.3%), Black or African American alone (13.4%), Asian alone (5.9%), Mixed Race (2.7%), American Indian or Alaska Native (1.3%), and Native Hawaiian or other Pacific Islander (0.2%).

The MTurk sample in the current study was similar to other MTurk samples in that the ethnic composition shows that MTurk samples were mostly White, with a higher percentage of the Asian group, and with lower percentages of the Blacks and Hispanics groups (Berinsky et al., 2012; Huff & Tingley, 2015; Paolacci & Chandler, 2014). Apart from the notable differences between the ratio of MTurk survey respondents and the corresponding U.S. population for the groups 'Black or African American alone' and

'Hispanic or Latino', the MTurk sample in this study is fairly representative of the U.S. population with respect to ethnic composition.

Annual Total Income. More than half of the MTurk respondents reported an annual income of $50,000 or more, made up of $50,000-$74,999 (27.1%) and $75,000 or more (25.7%). The other income groups and their corresponding percentages were $35,000-$49,999 (16.4%), $20,000-$34,999 (16.1%), $10,000-$19,999 (7.1%), and $9,999 or less (3.8%). A further 3.8% of respondents chose not to respond to this question. For the U.S. population, the most recent income data from the U.S. Census Bureau is the 2018 Current Population Survey (CPS) Annual Social and Economic (ASEC) Supplement. The data shows that the highest group is $75,000 or more (42.9%) followed by $50,000-$74,999 (17.2%). Other groups are $35,000-$49,999 (12.0%), $20,000-$34,999 (13.2%), $10,000-$19,999 (8.8%), and 5.9% for the group $9,999 or less (U.S. Census Bureau, 2019b).

Results therefore showed that the average income figure of $60,998 for the MTurk respondents in this study is lower than the average income figure of $90,021 for the U.S. population. The median income of $50,000 for the MTurk survey respondents in this study is also less than the reported median income for the U.S. population of $63,179 (U.S. Census Bureau, 2019b).

Previous Use of Facial Recognition Technology at Airport. Respondents were asked whether they had any prior use of facial recognition technology for the purpose of identification and verification at an airport. The purpose of the question was to give the researcher a general idea of the level of awareness of respondents with biometric devices at airports. Majority of the respondents (79.8%) reported no prior use of facial recognition technology at an airport, 9.7% stated that they had used the technology only once, while 10.2% stated that they had used the technology more than once. The results possibly reflected the novelty of the technology. While there was no known study to directly compare the results, the study by UNISYS (2019) found that 51% of U.S. consumers were willing to support the use of facial recognition technology to verify their identity for the purpose of security or for boarding an aircraft.

Effect of COVID-19 Crisis on Intentions. This question requested respondents to signify whether the COVID-19 crisis would have any effect on their perception of intention to use biometrics at airports. The majority of respondents (81%) stated that the COVID-19 crisis would not have an effect, while 19% stated that the crisis would have an effect on their perception. Furthermore, respondents who stated that the crisis would have an effect were given the choice to provide additional comments to clarify their decision. Some of the additional comments on their perception of intention provided by respondents were: “I wonder if they clean the machines if people have to touch them or breathe near the surfaces”, “I worry that someone may cough on it and it doesn't get cleaned”, “Because biometrics make sense to measure when there is a pandemic”, “If someone has the physical signs of coronavirus evident by biometrics, they should not be allowed on a plane”, “I don’t want to touch anything in an airport”, and “I would rather be in contact with less people. If I can go through an airport with minimal contact that would make me happy”. Other comments include “I'm more inclined to take advantage of these features now due to the pandemic”, “I think using biometrics is one of way staying contact free, which will help curb the spread of covid-19 virus”, “While I am not overly concerned of the virus, I like the security of biometrics. I use them in my home now and love them”, and “It allows me to social distance myself from airport workers”.

Finally, respondents were also allowed to state any additional comments on the use of biometrics. Some of the additional comments received were “I believe that when they work biometrics can be very useful, but there are privacy concerns that need to be addressed”, “I would want to be positive my data and information is 100% secure and I have say over how it's used”, “I think this is the next logical advancement, whether people are concerned about it or not”, “As long as the data is kept secure, then I would use it”, “It seems like a good idea to make an airport more efficient”, “I worry about inaccuracy, especially for people of color”, and “I think it's an interesting concept but it needs to be used carefully or there are many different ways in which it could be abused”. Table 17 shows an analysis of the type and numbers of additional comments received from respondents on the effect of the COVID-19 crisis and comments about the survey.

Other comments recorded include “I wouldn't mind as long as there's a way for me to choose not to use it, like having a separate line through security or, an opt out for check-in/boarding”, “If it would make the process of clearing security easier, I would certainly be willing to try a biometrics screening”, “May use biometrics if it was super simple, if it didn't work simply and easily, I would not use it”, and “I've used them, eventually it won't be a choice”.

From the additional comments received, it appears that while respondents may have some concerns, they were generally willing to utilize biometrics for identification and verification purposes. In addition, their comments also revealed that the COVID-19 pandemic would not really affect their perception of intention to use biometrics.

Table 17

Details of Additional Comments

Classification of Comments	Responses	Percentage of Respondents
Positive comments on effect of COVID -19 crisis on perception of intention to use biometrics	61	8.9%
Neutral comments on effect of COVID -19 crisis on perception of intention to use biometrics	37	5.4%
Negative comments on effect of COVID -19 crisis on perception of intention to use biometrics	30	4.3%
No additional comments on effect of COVID -19 crisis on perception of intention to use biometrics	561	81.4%
Total for comments on COVID – 19	689	100%
Positive comments about the survey or about biometrics	140	20.3%
Neutral comments about the survey or about biometrics	65	9.4%
Negative comments about the survey or about biometrics	92	13.4%
No comments about the survey or about biometrics	392	56.9%
Total for comments on survey or biometrics	689	100%

Non-Response Bias Test. Non-response bias measures how non-respondents influence the survey by comparing the characteristics of non-respondents against those who completed the survey. In this study, non-respondents were classified as those who did not answer two or more questions and those that were classified as unengaged. A Chi-square test was conducted to determine if there were any notable differences in the demographic attributes between respondents and non-respondents. From the results of the Chi-square test shown in Table 18, none of the probability (p) values of the demographic attributes is less than the designated p-value of .05. The results for all attributes are therefore non-significant and indicate that there are no clear differences between the data for persons that responded and non-respondents and suggests that the final sample was unaffected by non-response bias.

Table 18

Chi-Square Test for Non-Response Bias of Respondents Against Non-Respondents

Attribute	Chi-Square ($\chi 2$)	Probability (p)	Significant (Yes/No)
Effect of COVID-19 crisis on intention	2.177	.140	No
Age	37.333	.984	No
Gender	1.774	.621	No
Education	3.222	.666	No
Ethnicity	10.310	.172	No
Income	157.847	.702	No
Previous use of facial recognition	1.294	.731	No

Note. p is significant at $p < .05$.

Descriptive Statistics. The descriptive statistics presented for the factors (constructs) include mean, standard deviation (*SD*), kurtosis, and skewness. The current study examined attitudes, subjective norms, perceived behavioral control, perceived ease of use, and perceived usefulness as the influencing factors of passengers' behavioral intentions to use biometric technologies at airports. The study also investigated the moderating influence of privacy on the factors, while a COVID-19 factor was included as a control variable that could affect behavioral intentions.

Each factor in the questionnaire was evaluated by three or four item questions with respondents required to select their responses on a 5-point Likert-type scale with scores allocated as follows: 'strongly disagree' (-2), 'disagree'(-1), 'neutral' (0), 'agree' (+1), and 'strongly agree' (+2). A summary of the descriptive statistics of the constructs and item questions is presented in Table 19.

Calculating the average mean and average *SD* for each construct provided a broad appraisal of the influence of each factor on passengers' behavioral intentions to use biometric technologies at airports. An overall assessment of the average mean for each of the constructs shows that the values were all positive and within 'neutral' to 'agree', and ranged from .13 (subjective norms) to .97 (perceived usefulness).

Table 19

Descriptive Statistics for Constructs and Item Questions

Constructs	Item Questions	Mean (N = 689)	Average Mean for Construct	*SD*	Average *SD* for Construct	Skewness	Kurtosis
AT	AT1	.56	.47	1.197	1.205	-.647	-.459
	AT2	.48		1.197		-.583	-.533
	AT3	.47		1.271		-.594	-.707
	AT4	.36		1.153		-.416	-.515
SN	SN1	.16	.13	1.055	1.071	-.152	-.422
	SN2	.11		1.088		-.134	-.502
	SN3	.11		1.070		-.164	-.454
PB	PB1	1.04	.80	0.890	1.009	-1.215	1.992
	PB2	.43		1.239		-.346	-.979
	PB3	.93		0.896		-.937	.986
PE	PE1	.80	.93	0.989	0.911	-.767	.199
	PE2	.97		0.877		-.936	1.157
	PE3	.96		0.902		-1.014	1.322
	PE4	.99		0.876		-.896	.841
PU	PU1	1.07	.97	0.883	0.927	-1.158	1.643
	PU2	.97		0.920		-1.018	1.132
	PU3	.88		0.978		-1.045	.984
CV	CV1	.35	.38	1.232	1.250	-.418	-.884
	CV2	.44		1.242		-.494	-.828
	CV3	.35		1.277		-.431	-.974
PR	PR1	.65	.66	1.252	1.256	-.549	-.887
	PR2	.66		1.253		-.562	-.902
	PR3	.65		1.264		-.571	-.879
IN	IN1	.27	.16	1.172	1.168	-.486	-.657
	IN2	.15		1.160		-.364	-.744
	IN3	.08		1.172		-.258	-.834

Note. AT = Attitudes; SN = Subjective Norms; PB = Perceived Behavioral Control; PE = Perceived Ease of Use; PU = Perceived Usefulness; CV = Coronavirus (COVID-19); PR = Privacy Concerns; IN = Intention to Use.

Perceived usefulness (PU) had the highest average mean for all constructs at .97 and an average *SD* of .927. The result implies that the respondents on average had a positive belief of the usefulness of biometrics that was closer to ‘agree’ than ‘neutral’. It was noted that the item PU1 (“Using biometric systems would enable me conduct airport identification and verification processes quickly”) had the highest mean for all items (1.07) which is still closer to ‘agree’ than ‘strongly agree’. Perceived ease of use (PE) had the next highest average mean for constructs of .93 and an average standard deviation of .911. The results for this construct were also similar to perceived usefulness (PU) and possibly reflect the fact that both PU and PE are causally related variables of the technology acceptance model (TAM) by Davis et al. (1989).

Perceived behavioral control (PB) had an average mean for constructs of .80 and an average *SD* of 1.009, which means respondents rated their perceived control of making the decision to use biometrics closer to ‘agree’ than ‘neutral’. Item PB1 (“I would be able to use biometrics at airports”) had the second highest mean across all items (1.04). However, with item PB2’s (“The choice to use biometrics at airports is entirely up to me”) item mean of .43 and *SD* of 1.239, the PB construct had the highest variability across item means and item *SD* within constructs.

The last construct with an average mean that was closer to ‘agree’ than ‘neutral’ was privacy concerns (PR), with average mean for all constructs (.66) and average standard deviation (1.256). This shows that respondents were fairly positive regarding their personal information while using biometrics. Furthermore, the three items of this construct indicated very similar results and had the lowest variability across the item means within constructs.

The remaining four constructs all had average means that were closer to ‘neutral’ than ‘agree’. Attitudes (AT) had an average mean for all constructs (.47) and average standard deviation (1.205), COVID-19 (CV) had an average mean for all constructs (.38) and average standard deviation (1.250), while intention to use (IN) had an average mean for all constructs (.16) and average standard deviation (1.168). The construct with the lowest average mean was subjective norms (SN) at .13 and average standard deviation (1.071). In addition, all the three items of the construct had similar results while the construct had the second lowest variability across item means within constructs.

An initial evaluation of normality was carried out using skewness and kurtosis values in the output from IBM ® SPSS ®, as shown in Table 19. Skewness values for the item questions ranged from SN2 (-.134) to PB1 (-1.215). All the item questions displayed negative skewness values which indicates that the distribution of the data is unbalanced and is shifted to the right. For kurtosis, the items displayed both positive kurtosis (leptokurtic) and negative kurtosis (platykurtic). Of the 26 item questions, nine items were leptokurtic while 17 items were platykurtic. The positive kurtosis values ranged from PE1 (.199) to PB1 (1.992), while the negative kurtosis values ranged from SN1 (-.422) to PB2 (-.979).

A generally accepted assessment considers skewness and kurtosis values between +1 and -1 as acceptable to meet the assumption of normality. With this assessment, six question items (PB1, PE2, PE3, PU1, PU2, and PU3) violated the criteria for the assumption of normality. However, the additional assessments that were conducted to check for normality suggested that the data could be considered to have met the normality assumption. These include Hair et al. (2015), who noted that normality is acceptable with absolute values of skewness and kurtosis between +1.96 and −1.96 for a .05 significance level, and Singh and Sharma (2016) who stated normality is acceptable with absolute values of skewness and kurtosis between +2 and −2. All the skewness and kurtosis values meet the criteria of Singh and Sharma (2016), while only kurtosis value for PB1 (1.992) is not within the range of the criteria of Hair et al. (2015).

Confirmatory Factor Analysis (CFA). The CFA process using IBM ® SPSS ® AMOS v24 included initial data screening and analysis and concluded with an evaluation of the results, as detailed in this section. In the hypothesized model as shown in Figure 6, covariances were added between all latent variables (constructs); each observed variable was loaded on only one factor, while error terms associated with each observed variable were uncorrelated.

Normality. A secondary assessment of normality was conducted by examining the kurtosis values from the results of the analysis of the CFA model. From the AMOS output, the absolute values of kurtosis were between PB1 (+1.969) and PB2 (-.980). As was noted earlier in the study, kurtosis values below 7 are indicative of data normality (Byrne, 2016). It was therefore determined that the data met the assumption of normality and there was no need to transform the variables.

Missing Data. There were 51 missing values identified from the total of 17,914 possible answers to the Likert-Scale questions, representing 0.29% of the total data items. Two steps were used to treat missing data in this study. First, the eight cases with two or more missing values (indicating that respondents did not respond to two or more of the Likert scale questions), were deleted from further analysis. Second, the 33 other cases with only one missing value each had the missing values replaced with valid values from similar observations in the sample. The new values were thus retained for the analysis. A sample of 689 complete responses was therefore used to conduct the CFA process.

Outliers. Outliers were checked by examining the observations farthest from the centroid (Mahalanobis distance) values from the AMOS output. Outliers are classified as cases with a Mahalanobis distance (D^2) value distinct from other values or those with D^2 values above 100. While there was no case with a D^2 value that could be considered distinct from the other values, there were eight cases above 100 that were considered for deletion from the dataset. To determine whether to retain or delete the outliers, an assessment was conducted by deleting one outlier each time and conducting the CFA process again to check the effect on the total number of outliers, overall model fit, reliability, and validity. From the assessment, it was noted from the AMOS output that the number of outliers initially decreased from eight to seven, and then to six before increasing to seven. At each stage, there was no significant change in the overall fit, reliability, or validity of the model.

Since deleting the outliers did not significantly improve the analysis and considering that the cases were not significantly distinct from the other values, it was decided to retain the outliers for the analysis. Hair et al. (2015) also noted that deleting outliers may limit the generalizability of the analysis.

Model Evaluation. An evaluation of the CFA model fit was performed using Goodness-of-fit (GOF) indices. The results of the model fit summary from AMOS and the standard values are presented in Table 20.

Table 20

Fit Indices for Main Study - First CFA Model

Indices	Standard Values	Results	Acceptable (Yes/No)
CFI	≥0.95	0.974	Yes
GFI	≥0.90	0.928	Yes
AGFI	≥0.90	0.906	Yes
NFI	≥0.90	0.958	Yes
RMSEA	≤0.05	0.047	Yes
Normed Chi-Square ($\chi2$ /df)	$1<\chi2/df<3$	2.504	Yes

A comparison of the results against the standard values shows that the model fit was acceptable according to all the selected indices. However, as noted by Brown (2006), the evaluation of a CFA model should not be completed only on the basis of goodness of fit. Therefore, the next step involved checking for reliability and validity of the model. Construct Reliability (CR) was calculated with the aid of Microsoft Excel ® using the standardized regression weights (factor loadings) and the error variances from the AMOS output. Table 21 shows the results of the analysis.

Table 21

Reliability Analysis and Validity for Main Study - First CFA Model

Constructs	Item Questions	Factor Loadings(≥.5)	CR (≥.7)	α (≥.7)	AVE (≥.5)	MSV (<AVE)
Attitudes	AT1	.937	.940	.937	.796	.780
	AT2	.921				
	AT3	.922				
	AT4	.780				
Subjective Norms	SN1	.886	.930	.930	.816	.526
	SN2	.931				
	SN3	.893				
Perceived Behavioral Control	PB1	.811	.712	.650*	.471*	.599*
	PB2	.394*				
	PB3	.774				
Perceived Ease of Use	PE1	.763	.896	.893	.683	.599
	PE2	.843				
	PE3	.877				
	PE4	.864				
Perceived Usefulness	PU1	.851	.880	.877	.709	.552
	PU2	.851				
	PU3	.824				
Coronavirus (COVID-19)	CV1	.895	.911	.911	.774	.055
	CV2	.905				
	CV3	.838				
Privacy	PR1	.917	.940	.940	.840	.317
	PR2	.909				
	PR3	.923				
Intention to Use	IN1	.928	.941	.941	.843	.780
	IN2	.907				
	IN3	.919				

Note. * Indicates unacceptable reliability or validity value.

The factor loadings were examined as an indicator of possible problems with the model. Per the suggestion by Hair et al. (2015), factor loadings of at least 0.5 and ideally 0.7 or higher show a high association between the indicators and their associated constructs and indicate satisfactory construct validity. As with the first pilot study, the factor loading for item PB2 (.394) was the lowest among all the factor loadings and the only one below 0.5. All other factor loadings were above 0.7. While the calculated construct reliability values for all constructs were above the reference value of 0.7, the Cronbach's Alpha (as a measure of reliability) of the perceived behavioral control (PBC) construct was lowest at 0.650 and below the reference value of 0.7. The convergent validity, measured by the average variance extracted (AVE) was also lowest for this construct at .471 and less than the reference figure of 0.5 suggested by Hair et al. (2015). Table 21 also shows that all the maximum shared variance (MSV) values are lower than the associated AVE values for the constructs, except the PBC construct which indicates that there are concerns with the discriminant validity of the model.

The other measure to present the assessment of discriminant validity is shown in Table 22. To assure discriminant validity, the square roots of the AVE for any construct should be greater than the inter-construct correlations.

Table 22

Discriminant Validity for Main Study - First CFA Model

	CV	AT	SN	PB	PE	PU	PR	IN
CV	0.880*							
AT	0.151	0.892*						
SN	0.235	0.725	0.904*					
PB	0.022	0.468	0.372	0.686**				
PE	0.016	0.494	0.367	0.774	0.827*			
PU	0.120	0.743	0.531	0.608	0.637	0.842*		
PR	0.051	-0.552	-0.379	-0.175	-0.268	-0.330	0.916*	
IN	0.182	0.883	0.710	0.412	0.442	0.658	-0.563	0.918*

Note. * Indicates Square root of AVEs **Indicates unacceptable value for validity measure.

From this assessment, it is seen that the square root of the AVEs are greater than the inter-construct correlations for all constructs except for the PBC construct. Therefore, although the model fit for the CFA model was acceptable, it did not demonstrate acceptable reliability and construct validity. It is noted that following the poor factor loading of the PB2 item in the first pilot study, the rewording of the item resulted in acceptable reliability and validity of the model in the second pilot study. However, the item again recorded poor factor loading and unacceptable measures for reliability and validity in the main study.

Hair et al. (2015) noted that an item could be deleted from a model if the item has a low factor loading or if the item performs poorly regarding model integrity, model fit, or construct validity. They also advised that the literature should be considered in making any model modifications. Additional considerations were also necessary regarding the PBC construct specifically since the construct was composed of three items. While Hair et al. (2015) suggested there should be at least three items per factor, they also recognize that the principle of parsimony allows the use of the smallest number of items to sufficiently represent a construct. Therefore, the literature was consulted to examine whether there could be instances to support the deletion of the PB2 item ("The choice to use biometrics at airports is entirely up to me") from the model and thus use only two items to assess the PBC construct.

Marsh, Hau, Balla, and Grayson (1998) considered the number of indicators in a factor for a CFA model and concluded that there could be times when two indicators may be sufficient. Furthermore, Kline (2011), while assessing some rules for standard CFA models, noted that two indicators per factor was the minimum for model identification. Finally, while Eisinga, Grotenhuis, and Pelzer (2013) emphasized that more items per construct was better, they acknowledged that it was common for researchers to remove poor quality items from a limited pool and that could result in a scale having only two items.

Another consideration in the decision to delete the PB2 item involved an examination of the covariances from the AMOS output. The examination was guided by Hair et al. (2015) who suggested that two items with significant between-construct error covariances between them could be significantly more connected than what the initial measurement model predicted. In the same manner, Byrne (2016) noted that a high degree of overlap in contents of items can result in significant error covariances and create a redundancy where an item that is worded differently essentially asks the same question. While there were two other high values of within-construct error covariance terms, the highest between-construct error covariance was associated with items AT4 (“Using biometrics at airports would be pleasant”) and PB2 (“The choice to use biometrics at airports is entirely up to me”), (e4 <--> e9; MI= 29.929), which could suggest possible redundancy. It is possible that respondents associated the sense of satisfaction from a pleasant use of biometrics with the belief of having made a right choice between different options.

Thus, item PB2 (“The choice to use biometrics at airports is entirely up to me”) was deleted from the model, and the CFA process was conducted again to check if that could provide a solution to the reliability and validity problems. From the summary presented in Table 23, the model fit was also acceptable, same as with the first CFA model. All the model fit indices recorded improved values, which implies that the model fit was slightly better with the PB2 item removed.

Table 23

Fit Indices for Main Study - Second CFA Model

Indices	Standard Values	Results	Acceptable (Yes/No)
CFI	≥0.95	0.977	Yes
GFI	≥0.90	0.934	Yes
AGFI	≥0.90	0.913	Yes
NFI	≥0.90	0.962	Yes
RMSEA	≤0.05	0.046	Yes
Normed Chi-Square ($\chi 2$ /df)	$1<\chi 2/df<3$	2.425	Yes

In addition to the model fit indices, the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) values from AMOS were also compared between the default model with the PB2 item retained and the default model with the item removed. The model with the PB2 item removed had a better fit for the data as it had lower values (AIC 754.891; BIC 1108.640) than the model with the PB2 item retained (AIC 838.652; BIC 1201.472).

The next check involved the assessment for reliability and validity using the output from AMOS. The results as presented in Table 24 show that factor loadings for all constructs were above the reference value. Cronbach's Alpha for the PBC construct improved from .650 to .771, while the AVE improved from .471 to .629. All the observed values were above the reference values. The observed MSV value of .601 is also less than the AVE value.

Table 24

Reliability Analysis and Validity for Main Study - Second CFA Model

Constructs	Item Questions	Factor Loadings(≥.5)	CR (≥.7)	α (≥.7)	AVE (≥.5)	MSV (<AVE)
Attitudes	AT1	.937	.940	.937	.796	.780
	AT2	.921				
	AT3	.922				
	AT4	.780				
Subjective Norms	SN1	.886	.930	.930	.816	.526
	SN2	.931				
	SN3	.893				
Perceived Behavioral Control	PB1	.817	.772	.771	.629	.601
	PB3	.769				
Perceived Ease of Use	PE1	.762	.896	.893	.683	.601
	PE2	.843				
	PE3	.864				
	PE4	.833				
Perceived Usefulness	PU1	.851	.880	.877	.709	.552
	PU2	.851				
	PU3	.824				
Coronavirus (COVID-19)	CV1	.895	.911	.911	.774	.055
	CV2	.905				
	CV3	.838				
Privacy	PR1	.917	.940	.940	.840	.317
	PR2	.909				
	PR3	.923				
Intention to Use	IN1	.928	.941	.941	.843	.780
	IN2	.907				
	IN3	.919				

To complete the validity check, the discriminant validity was assessed according to the same criteria used earlier. From the results as presented in Table 25, the square roots of the AVEs are all greater than the inter-construct correlations. The second CFA model with the PB2 item removed demonstrated acceptable reliability and construct validity (as assessed using convergent validity and discriminant validity).

Table 25

Discriminant Validity for Main Study - Second CFA Model

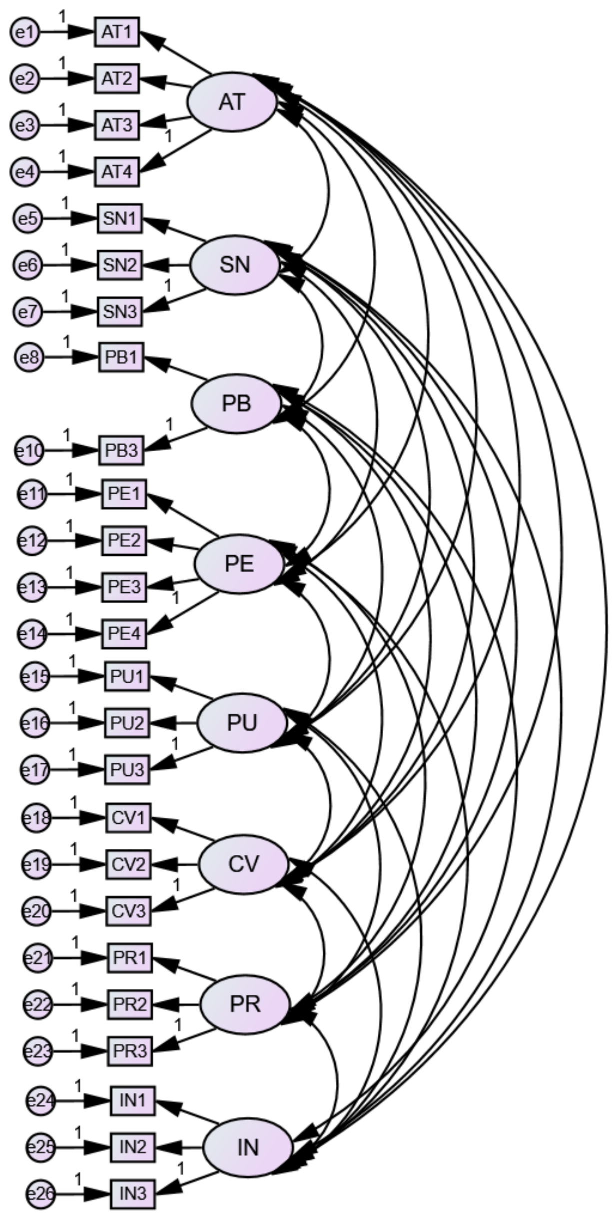
	CV	AT	SN	PB	PE	PU	PR	IN
CV	0.880*							
AT	0.151	0.892*						
SN	0.235	0.725	0.904*					
PB	0.012	0.459	0.352	0.793*				
PE	0.016	0.494	0.367	0.775	0.826*			
PU	0.120	0.743	0.531	0.606	0.637	0.842*		
PR	0.051	-0.552	-0.379	-0.169	-0.268	-0.330	0.916*	
IN	0.182	0.883	0.710	0.396	0.442	0.658	-0.563	0.918*

Note. * Indicates Square root of AVEs.

The second CFA model with the PB2 item removed was therefore selected as the final re-specified CFA model, as shown in Figure 7. This model was used for the structural model assessment.

Figure 7

Final Re-Specified CFA Model with PB2 Item Deleted

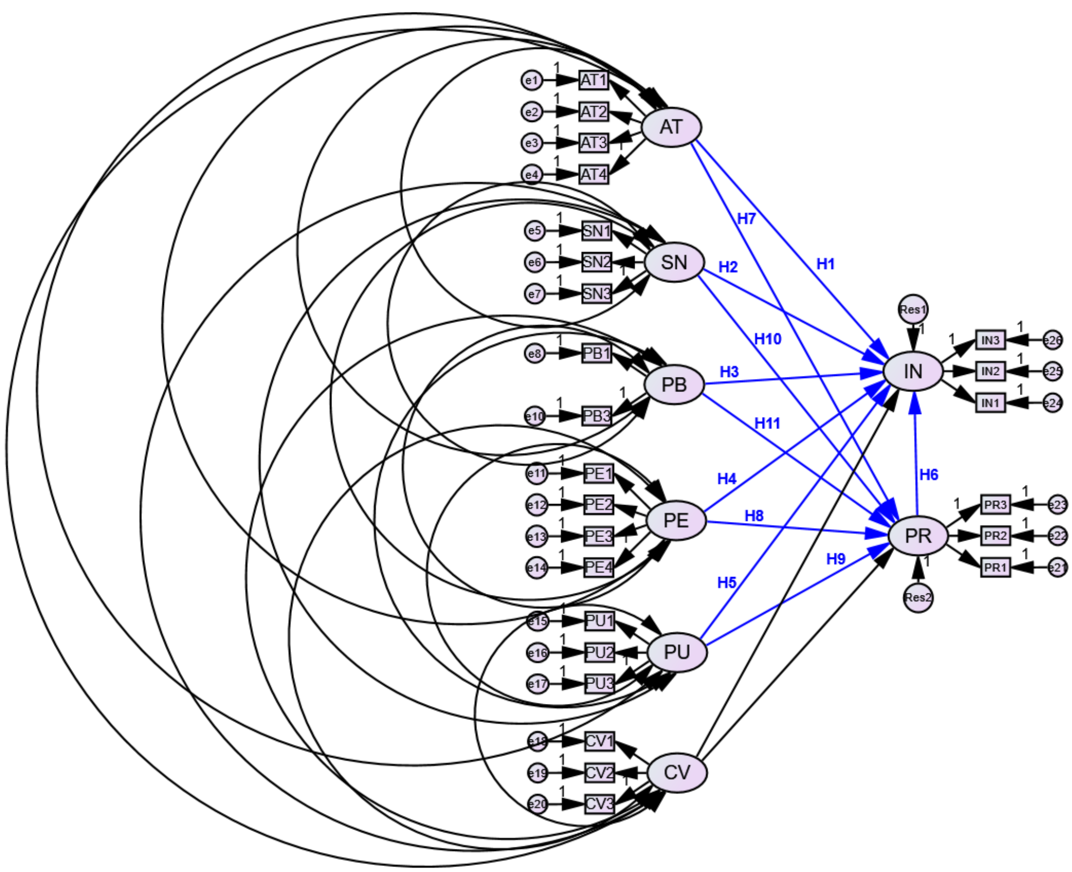


Note. AT = Attitudes; SN = Subjective Norms; PB = Perceived Behavioral Control; PE = Perceived Ease of Use; PU = Perceived Usefulness; CV = Coronavirus (COVID-19); PR = Privacy Concerns; IN = Intention to Use.

Structural Equation Modeling (SEM). The third step involved the completion of SEM using IBM ® SPSS ® AMOS v24. While the CFA model is considered a measurement model that represents all constructs and the relationships among them, the SEM model enables the application of the structural theory by detailing the related constructs and the type of each relationship (Hair et al., 2015).

Figure 8

Initial SEM Model (No Interaction Effects)



Note. AT = Attitudes; SN = Subjective Norms; PB = Perceived Behavioral Control; PE = Perceived Ease of Use; PU = Perceived Usefulness; CV = Coronavirus (COVID-19); PR = Privacy Concerns; IN = Intention to Use.

The structural model shown in Figure 8 was developed from the re-specified CFA model by deleting covariances between factors, connecting independent (exogenous) variables by correlations (double-headed curved arrows), fixing residual items to dependent (endogenous) variables, and inserting one-way arrow symbols to represent hypotheses. Hypotheses for the study are labeled and color coded in blue. Following the suggestion by Becker (2005) and Judge and Bono (2000), the control variable was treated like one of the independent variables and was also added to the hypotheses for the study.

Model Evaluation. The evaluation of the SEM model followed the same process that was used in the CFA model to assess for normality and also used the same GOF indices to evaluate model fit. From the AMOS output, all kurtosis values met the criteria for data normality while there was no case with a Mahalanobis distance (D^2) value that was considered distinct from other values.

Table 26

Fit Indices - Initial SEM Model

Indices	Standard Values	Results	Acceptable (Yes/No)
CFI	≥0.95	0.977	Yes
GFI	≥0.90	0.934	Yes
AGFI	≥0.90	0.913	Yes
NFI	≥0.90	0.962	Yes
RMSEA	≤0.05	0.046	Yes
Normed Chi-Square ($\chi2$ /df)	$1<\chi2/df<3$	2.425	Yes

As shown in Table 26, the model fit indices all displayed acceptable results, which shows that the SEM model fit was acceptable. The results for the SEM model were also similar to the results from the final re-specified CFA model fit, as can be seen in Table 23, therefore there was no requirement for model re-specification.

Hypotheses Testing – SEM Model Without Interaction Effects. Hypotheses testing for the SEM model involved analyzing the relationships from the AMOS output. A relationship is supported as statistically significant if the absolute value of the Critical Ratio (t-value) is greater than (>) 1.96 and the p-value is less than (<) .05. The standardized regression weights (estimates) were also used to assess the relative strengths of the relationship, while the unstandardized regression weights were used to report the change in the predicted variables for each unit change in the predictor. The results of the hypotheses testing for the SEM model without interactions are presented in Table 27 and discussed further in this section, while the SEM model with the unstandardized path coefficients is presented in Figure 9. The results show that of the eleven hypotheses, six were supported while the remaining five were not supported. The hypotheses that were supported are color coded in blue, while the hypotheses that were not supported are in black font. The results also show that the two hypotheses proposed for the control variable were supported.

Hypothesis 1 (H_1: Attitudes positively influence passengers' intentions) was supported with $t > 1.96$ ($t = 12.626$) and $p < .001$. The results also indicate that a one-point increase in attitude will lead to an increase in passengers' intentions to use biometrics by 0.821.

Hypothesis 2 (H_2: Subjective norms positively influence passengers' intentions) was supported with $t = - 4.164$ and $p < .001$. The results also show that a one-point increase in subjective norms will lead to an increase in passengers' intentions to use biometrics by 0.157.

Hypothesis 3 (H_3: Perceived behavioral control positively influences passengers' intentions) was not supported. The relationship was not significant (*p* = .730); absolute value of critical ratio <1.96 (*t* = -0.345), suggesting that perceived behavioral control was not considered a significant factor in passengers' intentions to use biometrics.

Table 27

Hypotheses Testing for Initial SEM Model (Without Interaction Effects)

Hypotheses	Estimates	*t*-value	*p*-value	Result
H_1: Attitudes positively influence intentions	.686	12.626	***	Supported
H_2: Subjective norms positively influence intentions	.140	4.164	***	Supported
H_3: Perceived behavioral control positively influences intentions	-.016	-.345	.730	Not Supported
H_4: Perceived ease of use positively influences intentions	.011	.240	.810	Not Supported
H_5: Perceived usefulness positively influences intentions	.031	.708	.479	Not Supported
H_6: Privacy concerns negatively influence intentions	-.124	-4.490	***	Supported
H_7: Attitudes negatively influence privacy concerns	-.705	-9.457	***	Supported
H_8: Perceived ease of use negatively influences privacy concerns	-.177	-2.458	.014**	Supported
H_9: Perceived usefulness negatively influences privacy concerns	.177	2.517	.012	*Not Supported
H_{10}: Subjective norms are related to privacy concerns	.008	.148	.882	Not Supported
H_{11}: Perceived behavioral control is related to privacy concerns	.180	2.394	.017**	Supported
Control Variable				
Effect of COVID-19 on passengers' behavioral intentions while controlling for the other variables	.048	2.107	.035**	Supported
Effect of COVID on passengers' privacy concerns while controlling for the other variables	.135	3.738	***	Supported

Note. *** $p < .001$. ** $p < .05$. *Hypothesis in reverse direction.

Hypothesis 4 (H_4: Perceived ease of use positively influences passengers' intentions) was not supported. The relationship was found to be not significant (p = 0.810), and t <1.96. This suggests that passengers did not consider perceived ease of use as an important factor in their intentions to use biometrics.

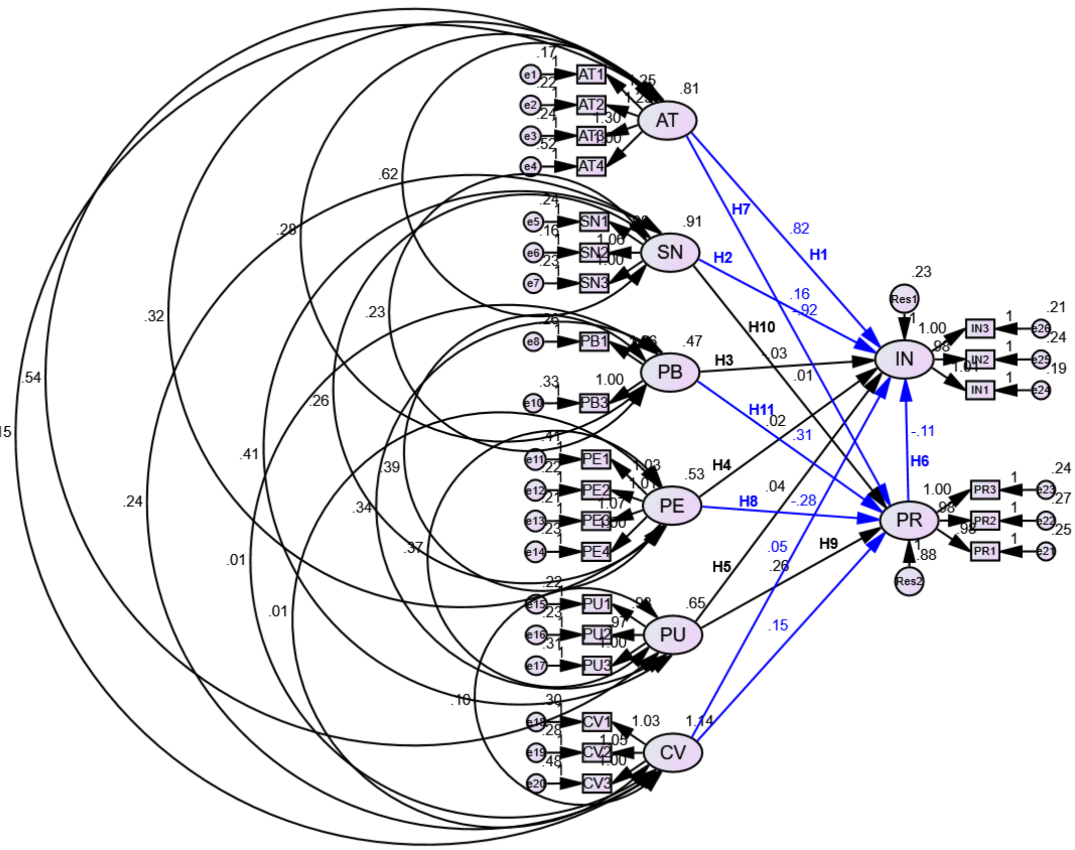
Hypothesis 5 (H_5: Perceived usefulness positively influences passengers' intentions) was not supported. The relationship was not significant (p = 0.479), and t =-0.708 (<1.96). This suggests that like perceived ease of use, passengers did not consider perceived usefulness as an important factor in their intentions to use biometrics.

Hypothesis 6 (H_6: Privacy concerns negatively influence passengers' intentions) was supported (p < .001), and absolute t >1.96 (t = -4.490). This implies that privacy concerns have a negative influence on passengers' intentions to use biometrics such that a one-point increase in privacy concerns will lead to a decrease in intentions by -0.114.

Hypothesis 7 (H_7: Attitudes negatively influence passengers' privacy concerns) was supported (p < .001), and absolute t >1.96 (t = -9.457), suggesting that attitudes have a negative influence on passengers' privacy concerns with the use of biometrics. From the estimate, a one-point increase in attitude will lead to a decrease in passengers' privacy concerns by -0.915.

Figure 9

Initial SEM Model (No Interactions) with Unstandardized Regression Weights Displayed, and Significant Paths Depicted in Blue



Note. AT = Attitudes; SN = Subjective Norms; PB = Perceived Behavioral Control; PE = Perceived Ease of Use; PU = Perceived Usefulness; CV = Coronavirus (COVID-19); PR = Privacy Concerns; IN = Intention to Use.

Hypothesis 8 (H_8: Perceived ease of use negatively influences passengers' privacy concerns) was supported. The relationship was significant at $p < .05$ ($p = .014$) and absolute $t > 1.96$ ($t = -2.458$). The results also indicate that a one-point increase in perceived ease of use will lead to a decrease in passengers' privacy concerns by -0.283.

Hypothesis 9 (H_9: Perceived usefulness negatively influences privacy concerns) was not supported. Although the relationship was statistically significant (p = .012) at the p < .05 level and t >1.96 (t = 2.517), the estimate did not follow the hypothesized direction. It is thus suggested that the relationship between perceived usefulness and privacy concerns is a positive one.

Hypothesis 10 (H_{10}: Subjective norms are related to privacy concerns) did not specify the direction of the proposed relationship between subjective norms and privacy concerns. The relationship was not supported as it was not statistically significant (p = 0.882), and t-value 0.148 (<1.96). This suggests that passengers did not consider subjective norms to be a major determinant of their privacy concerns with the use of biometric technologies.

Hypothesis 11 (H_{11}: Perceived behavioral control is related to privacy concerns) was also not specific with the direction of the proposed relationship. This hypothesis was supported (p = .017), and absolute t >1.96 (t = 2.394). Therefore, perceived behavioral control had a positive influence on privacy concerns with a one-point increase in perceived behavioral control leading to a 0.305 increase in privacy concerns.

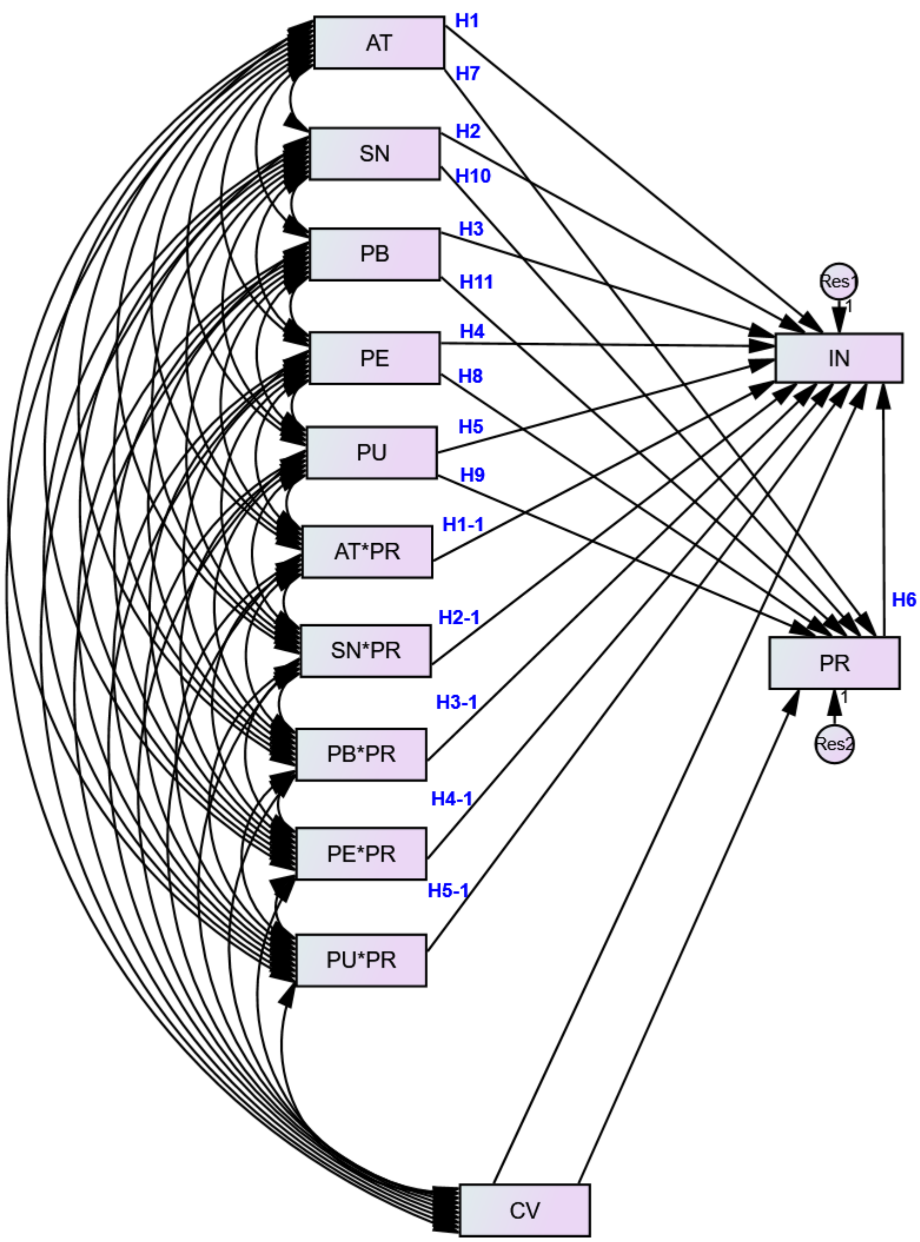
Control Variable. Becker (2005) recommended that the results of analyses should be reported with and without control variables. Thus, the effect of COVID-19 (CV) on passengers' behavioral intentions and passengers’ privacy concerns (the endogenous variables) while controlling for the other variables was determined by comparing the results of the hypotheses testing with the control variable in the model and the results without the control variable in the model. The CV variable was therefore removed from the model, following which the model evaluation and hypotheses testing were repeated.

The results without the CV variable indicated a good model fit [CFI=0.976; GFI=0.934; AGFI=0.911; NFI=0.964; RMSEA=0.051; Normed Chi-Square ($\chi2$ /df) = 2.761]; these values were similar to the model with the CV variable included. Next, a comparison of the results of the hypotheses tests for the two models showed that while there were slight differences in the estimates from the two models, all the hypotheses were in the same direction, indicating there was no change in all the relationships. Although the presence of the control variable could explain the slight differences, further study would be required to determine the extent of the impact of COVID-19 in the relationships. The results, however, suggest that there was no significant effect of COVID-19 on passengers' behavioral intentions and passengers' privacy while controlling for the other variables.

Hypotheses Testing – SEM Model with Moderation (Interaction) Effects. Prior to the hypothesis testing for the model with interaction effects, the SEM model was configured to allow the estimation of the moderation (or interaction effects) of the latent variables. The method used was similar to that used in multiple regression and involved creating product terms that are essentially the product of the scores from two different variables to represent the interaction effects (Kline, 2011; Williams, Vandenberg, & Edwards, 2009). First, the latent constructs were converted to composite factors using the regression imputation function in AMOS. This resulted in the creation of a new SPSS data file with eight new composite factors (PU, PE, PB, SN, AT, PR, IN).

Figure 10

SEM Model with Hypotheses and Interaction Effects Displayed



Note. AT = Attitudes; SN = Subjective Norms; PB = Perceived Behavioral Control; PE = Perceived Ease of Use; PU = Perceived Usefulness; CV = Coronavirus (COVID-19); PR = Privacy Concerns; IN = Intention to Use.

The next step was to create standardized values for the eight new variables. Finally, the values for the interaction variables were then computed using the products of the exogenous variables (PU, PE, PB, SN, AT) and the moderating variable (PR). The SEM model with the hypotheses and interaction effects is shown in Figure 10.

The analysis of the results followed the same process as the model without interactions explained in the previous section. As was the case with the model without interaction effects, the same six hypotheses proposed in the model were supported, while the same five hypotheses were not supported. Of the additional five hypotheses introduced for the interaction effects, three of the hypotheses were supported, while two were not supported. In addition, the two hypotheses proposed for the control variable were also supported. The results of the hypotheses testing for the SEM model with interactions are presented in Table 28 and discussed below, while Figure 11 shows the SEM model with the unstandardized path coefficients. The hypotheses that were supported are color coded in blue, while the hypotheses that were not supported are in black font.

Hypothesis 1 (H_1: Attitudes positively influence passengers' intentions) was supported with a t-value >1.96 ($t = 18.512$) and a p-value <.001. The results also indicate that a one-point increase in attitude will lead to an increase in passengers' intentions to use biometrics by 0.668.

Hypothesis 2 (H_2: Subjective norms positively influence passengers' intentions) was supported with a t-value of 5.052 and a p-value <.001. The results also show that a one-point increase in subjective norms will lead to an increase in passengers' intentions to use biometrics by 0.115.

Hypothesis 3 (H_3: Perceived behavioral control positively influences passengers' intentions) was not supported. The relationship was not significant (p = .563), absolute value of critical ratio <1.96 (t = -0.578), suggesting that passengers did not consider perceived behavioral control to be a major factor in their intentions to use biometrics.

Hypothesis 4 (H_4: Perceived ease of use positively influences passengers' intentions) was not supported. The relationship was not significant ($p = 0.370$), and t <1.96. This suggests that passengers did not consider perceived ease of use as an important factor in their intentions to use biometrics.

Hypothesis 5 (H_5: Perceived usefulness positively influences passengers' intentions) was not supported. The relationship was not significant ($p = 0.161$), and t= 1.402 (<1.96). This suggests that like perceived ease of use, passengers did not consider perceived usefulness as an important factor in their intentions to use biometrics.

Hypothesis 6 (H_6: Privacy concerns negatively influence passengers' intentions) was supported ($p < .001$), and absolute t >1.96 ($t = -8.109$). This implies that privacy concerns have a negative influence on passengers' intentions to use biometrics such that a one-point increase in privacy concerns will lead to a decrease in intentions by -0.149.

Hypothesis 7 (H_7: Attitudes negatively influence passengers' privacy concerns) was supported ($p < .001$), and the absolute t >1.96 ($t = -13.972$), suggesting that attitudes have a negative influence on passengers' privacy concerns with the use of biometrics. From the estimate, a one-point increase in attitude will lead to a decrease in passengers' privacy concerns by -0.853.

Table 28

Hypotheses Testing SEM Model with Interaction Effects

Hypotheses	Estimates	*t*-value	*p*-value	Result
H_1: Attitudes positively influence intentions	.666	18.512	***	Supported
H_2: Subjective norms positively influence intentions	.114	5.052	***	Supported
H_3: Perceived behavioral control positively influences intentions	-.017	-.578	.563	Not Supported
H_4: Perceived ease of use positively influences intentions	.028	.897	.370	Not Supported
H_5: Perceived usefulness positively influences intentions	.044	1.402	.161	Not Supported
H_6: Privacy concerns negatively influence intentions	-.149	-8.109	***	Supported
H_7: Attitudes negatively influence privacy concerns	-.853	-13.972	***	Supported
H_8: Perceived ease of use negatively influences privacy concerns	-.307	-5.089	***	Supported
H_9: Perceived usefulness negatively influences privacy concerns	.282	4.798	***	*Not Supported
H_{10}: Subjective norms are related to privacy concerns	.067	1.427	.153	Not Supported
H_{11}: Perceived behavioral control is related to privacy concerns	.283	4.720	***	Supported
Interactions				
$H_{1\text{-}1}$: The level of privacy concerns will moderate the positive relationship between attitudes and intentions	.172	5.310	***	Supported
$H_{2\text{-}1}$: The level of privacy concerns will moderate the positive relationship between subjective norms and intentions	-.044	-2.125	.034**	Supported
$H_{3\text{-}1}$: The level of privacy concerns will moderate the positive relationship between perceived behavioral control and intentions	-.036	-1.284	.199	Not Supported
$H_{4\text{-}1}$: The level of privacy concerns will moderate the positive relationship between perceived ease of use and intentions	.010	.348	.728	Not Supported
$H_{5\text{-}1}$: The level of privacy concerns will moderate the positive relationship between perceived usefulness and intentions	-.085	-2.718	.007**	Supported

Table 28 (*continued*)

Hypotheses	Estimates	*t*-value	*p*-value	Result
Control Variable				
Effect of COVID-19 on passengers' behavioral intentions while controlling for the other variables	.050	3.402	***	Supported
Effect of COVID on passengers' privacy concerns while controlling for the other variables	.109	3.537	***	Supported

Note. *** $p < .001$. ** $p < .05$. *Hypothesis in reverse direction.

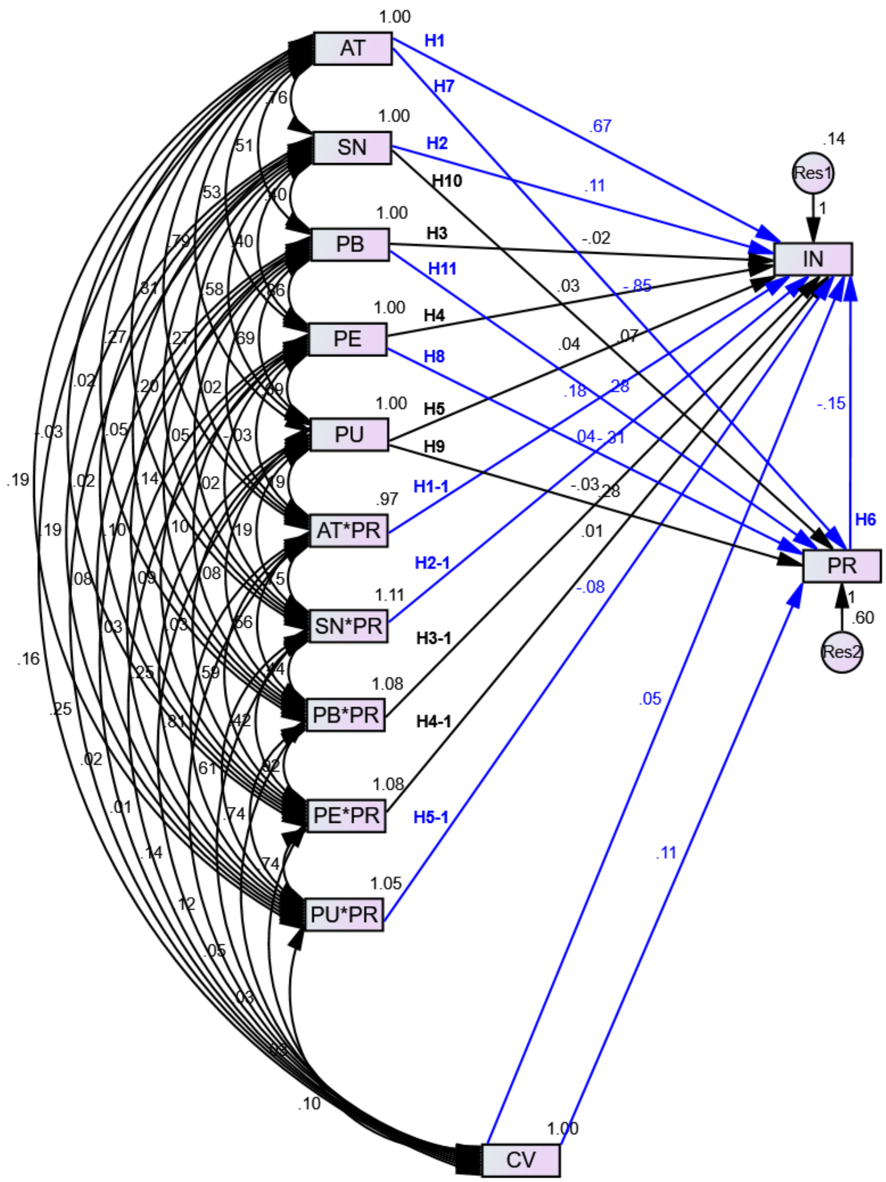
Hypothesis 8 (H_8: Perceived ease of use negatively influences passengers' privacy concerns) was supported ($p < .001$), and the absolute $t > 1.96$ ($t = -5.089$). The results also indicate that a one-point increase in perceived ease of use will lead to a decrease in passengers' privacy concerns by -0.307.

Hypothesis 9 (H_9: Perceived usefulness negatively influences privacy concerns) was not supported. Although there was a statistically significant relationship ($p < .001$), and $t > 1.96$ ($t = 4.798$), the estimate did not follow the hypothesized direction. It is thus suggested that the relationship between perceived usefulness and privacy concerns is a positive one.

Hypothesis 10 (H_{10}: Subjective norms are related to privacy concerns) did not specify the direction of the proposed relationship between subjective norms and privacy concerns. The relationship was not supported as it was not statistically significant ($p = 0.153$), and *t*-value 1.427 (<1.96). This suggests that passengers did not consider subjective norms to be a major determinant of privacy concerns with the use of biometric technologies.

Figure 11

SEM Model (Interaction Effects) with Unstandardized Regression Weights Displayed, and Significant Paths Depicted in Blue



Note. AT = Attitudes; SN = Subjective Norms; PB = Perceived Behavioral Control; PE = Perceived Ease of Use; PU = Perceived Usefulness; CV = Coronavirus (COVID-19); PR = Privacy Concerns; IN = Intention to Use.

Hypothesis 11 (H_{11}: Perceived behavioral control is related to privacy concerns) was also not specific with the direction of the proposed relationship. This hypothesis was supported ($p < .001$), and absolute t-value >1.96 ($t = 4.720$). Therefore, perceived behavioral control had a positive influence on privacy concerns with a one-point increase in perceived behavioral control leading to a 0.283 increase in privacy concerns.

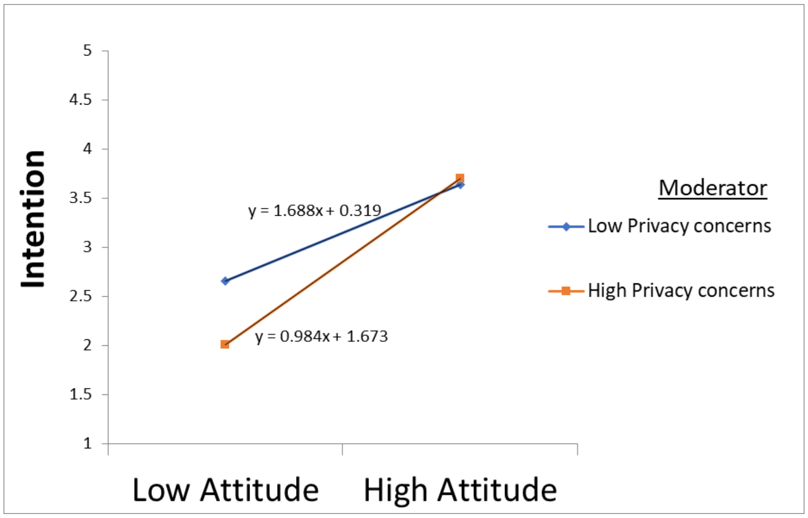
Moderations (Interaction Effects). The interaction effects were also assessed using the same criteria as the main hypotheses. As noted by Williams et al. (2009), the significance of the product of the latent variables provides the statistical test of the interaction of the variables. The significant interactions are shown in Figures 12-14.

$H_{1\text{-}1}$: The level of privacy concerns will moderate the positive relationship between attitudes and intentions. This hypothesis was supported. The interaction was found to be significant ($p < .001$), and $t= 5.310$. It was also seen from the results that privacy concerns strengthen the positive relationship between attitudes and intentions. A one-point increase in privacy concerns results in an increase in the interaction between attitudes and intentions by 0.176.

$H_{2\text{-}1}$: The level of privacy concerns will moderate the positive relationship between subjective norms and intentions. The hypothesis was supported, as the interaction was found to be significant ($p = 0.034$) at the $p < .05$ level, and absolute t > 1.96 ($t = -2.125$). Privacy concerns was found to dampen the positive relationship between subjective norms and intentions such that a one-point increase in privacy concerns results in a decrease in the interaction between subjective norms and intentions by -0.042.

Figure 12

Moderating Effect of Privacy on Relationship Between Attitudes and Intentions

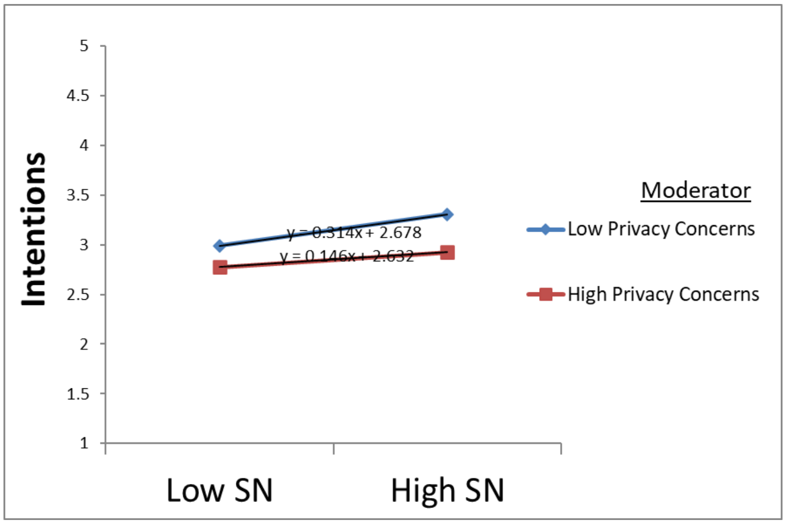


$H_{3\text{-}1}$: The level of privacy concerns will moderate the positive relationship between perceived behavioral control and intentions. This hypothesis was not supported since the interaction was found to be not significant ($p = 0.199$), and the absolute t <1.96 ($t = -1.284$). The results also suggest that there is a negative relationship between perceived behavioral control and intentions.

$H_{4\text{-}1}$: The level of privacy concerns will moderate the positive relationship between perceived ease of use and intentions. This hypothesis was not supported, despite the results showing a positive relationship between perceived ease of use and intentions. This is because the interaction was not significant ($p = 0.728$), and the absolute t-value <1.96 ($t = 0.348$).

Figure 13

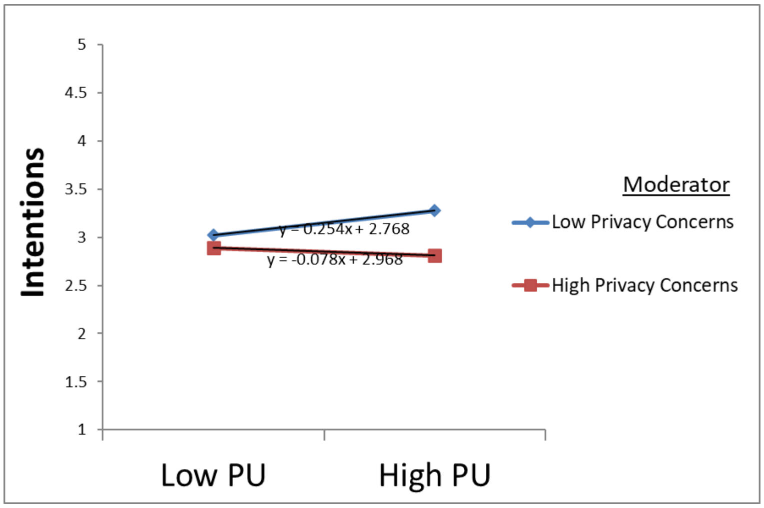
Moderating Effect of Privacy on Relationship Between Subjective Norms and Intentions



$H_{5\text{-}1}$: The level of privacy concerns will moderate the positive relationship between perceived usefulness and intentions. This hypothesis was supported as the interaction was found to be significant ($p = 0.007$) at the $p < .05$ level, and absolute t >1.96 ($t = -2.718$). Privacy concerns was found to dampen the positive relationship between perceived usefulness and intentions with a one-point increase in privacy concerns resulting in a reduction in the interaction between perceived usefulness and intentions by -0.083.

Figure 14

Moderating Effect of Privacy on Relationship Between Perceived Usefulness and Intentions



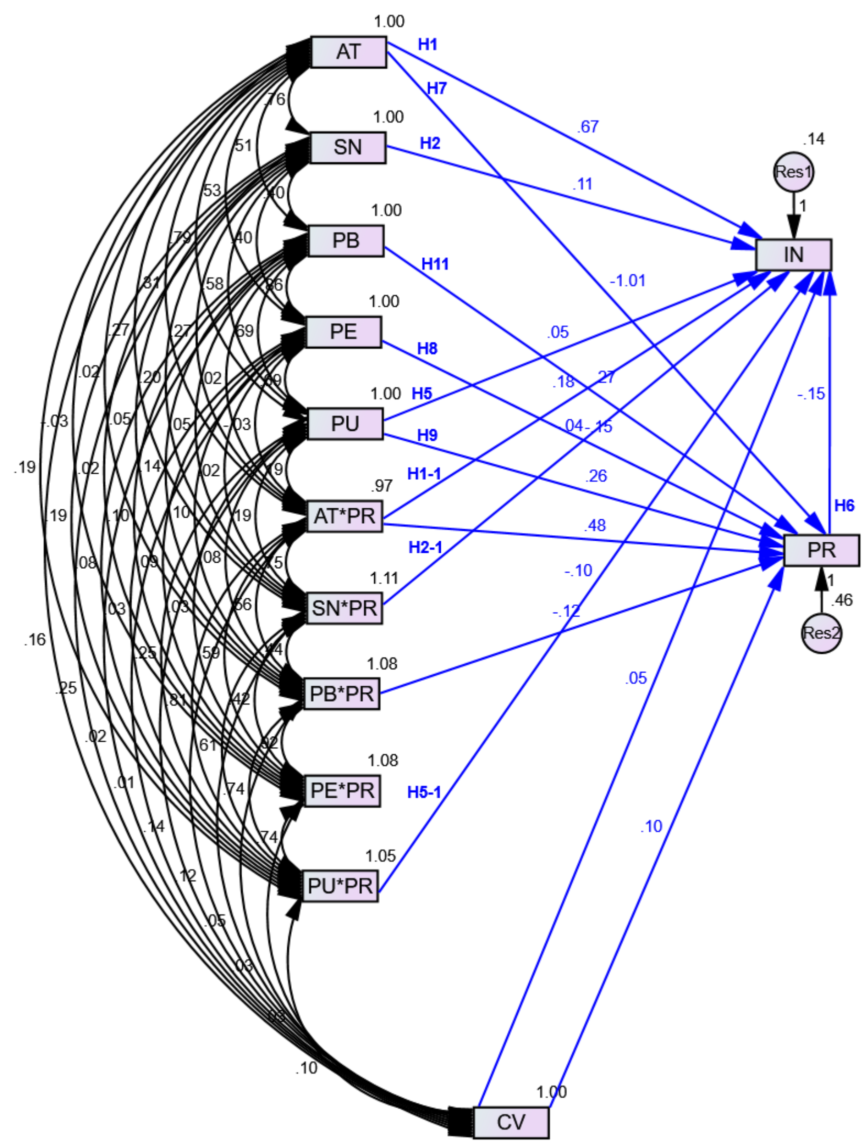
Model Fit for Modified SEM Model. The SEM model with interaction effects did not have a satisfactory model fit (CMIN/DF = 39.399, AGFI = 0.320, RMSEA = 0.236). A post-hoc analysis to improve the model fit involved trimming the model by removing the non-significant interaction effects. Following a step-by-step removal of the two interaction effects, there was a slight improvement in model fit (CMIN/DF = 28.446, AGFI = 0.515, RMSEA = 0.200). Next, the three non-significant paths were trimmed from the model one at a time. This resulted in a further improvement in model fit (CMIN/DF = 20.189, AGFI = 0.656, RMSEA = 0.167). Since there were no further non-significant interactions or paths that could be removed, the next focus was on the modification indices (MIs).

An examination of the MIs showed a high regression weight (MI = 123.607) for the path (ZPR <--- int_AT_PR), suggesting a cross-loading from the interaction variable to the privacy variable. A regression line was drawn, and the results showed a significant improvement in model fit (CMIN/DF = 4.103, AGFI = 0.919, RMSEA = 0.067). While this was evidence of an acceptable model fit, the next highest regression weight was also checked in case drawing a regression line for the path (ZPR <--- int_PB_PR) with MI = 8.631 could lead to further improvement in the model. The results showed a further improvement in model fit (CMIN/DF = 2.831, AGFI = 0.943, RMSEA = 0.052). In addition, there were no other regression weights from the results. This modified model is shown in Figure 15.

A comparison of the model fit between the initial SEM model and the modified SEM model, as shown in Table 29, reveals that all the fit indices for the modified SEM model improved and remained acceptable apart from the RMSEA, which at 0.052 was slightly above the standard value of 0.05. However, this value was still acceptable according to Hu and Bentler (1999), who noted that RMSEA between 0.05 and 0.10 was moderate, while Hair et al. (2015) noted that values of RMSEA of less than 0.07 with CFI of 0.92 or higher was an indication of good fit.

Figure 15

Modified SEM Model with Unstandardized Regression Weights Displayed



Note. AT = Attitudes; SN = Subjective Norms; PB = Perceived Behavioral Control; PE = Perceived Ease of Use; PU = Perceived Usefulness; CV = Coronavirus (COVID-19); PR = Privacy Concerns; IN = Intention to Use.

Table 29

Comparison of Fit Indices - Initial SEM Model and Modified SEM Model

Indices	Initial SEM Model	Modified SEM Model
CFI	0.977	0.998
GFI	0.934	0.995
AGFI	0.913	0.943
NFI	0.962	0.997
RMSEA	0.046	0.052
Normed Chi-Square ($\chi2$ /df)	2.425	2.831

Hypotheses Testing for Modified SEM Model. The hypotheses in the modified SEM model were assessed using the same criteria used for the initial SEM model. The results, as shown in Table 30, indicate that of the eleven hypotheses, six were supported, one was not supported, while four were removed. For the interaction effects, three hypotheses were supported, while two were removed from the model. A summary of the changes in the estimates of the initial and modified SEM models is presented in Table 31.

Table 30

Hypotheses Testing - Modified SEM Model

Hypotheses	Estimates	*t*-value	*p*-value	Result/ Remarks
H_1: Attitudes positively influence intentions	.669	17.454	***	Supported
H_2: Subjective norms positively influence intentions	.115	5.087	***	Supported
H_3: Perceived behavioral control positively influences intentions	-	-	-	Removed
H_4: Perceived ease of use positively influences intentions	-	-	-	Removed
H_5: Perceived usefulness positively influences intentions	-	-	-	Removed
H_6: Privacy concerns negatively influence intentions	-.150	-7.310	***	Supported
H_7: Attitudes negatively influence privacy concerns	-1.006	-21.996	***	Supported
H_8: Perceived ease of use negatively influences privacy concerns	-.150	-2.757	.006**	Supported
H_9: Perceived usefulness negatively influences privacy concerns	.259	5.024	***	*Not Supported
H_{10}: Subjective norms are related to privacy concerns	-	-	-	Removed
H_{11}: Perceived behavioral control is related to privacy concerns	.275	5.195	***	Supported
Interactions				
H_{1-1}: The level of privacy concerns will moderate the positive relationship between attitudes and intentions	.472	13.230	***	Supported
H_{2-1}: The level of privacy concerns will moderate the positive relationship between subjective norms and intentions	-.046	-2.189	.029**	Supported
H_{3-1}: The level of privacy concerns will moderate the positive relationship between perceived behavioral control and intentions	-	-	-	Removed
H_{4-1}: The level of privacy concerns will moderate the positive relationship between perceived ease of use and intentions	-	-	-	Removed
H_{5-1}: The level of privacy concerns will moderate the positive relationship between perceived usefulness and intentions	-.105	-3.903	***	Supported
Control Variable				
Effect on passengers' behavioral intentions while controlling for the other variables	.050	3.379	***	Supported
Effect on passengers' privacy concerns while controlling for the other variables	.097	3.665	***	Supported

Note. *** $p < .001$. ** $p < .05$ *Hypothesis in reverse direction.

Table 31

Changes in Estimates from Initial SEM Model to Modified SEM Model

Hypotheses	Initial SEM Model Estimates	Modified SEM Model Estimates	Change/ Remarks
H_1: Attitudes positively influence intentions	.666	.669	.003↑
H_2: Subjective norms positively influence intentions	.114	.115	.001↑
H_3: Perceived behavioral control positively influences intentions	-.017	-	Removed
H_4: Perceived ease of use positively influence intentions	.028	-	Removed
H_5: Perceived usefulness positively influences intentions	.044	-	Removed
H_6: Privacy concerns negatively influence intentions	-.149	-.150	.001↑
H_7: Attitudes negatively influence privacy concerns	-.853	-1.006	.153↑
H_8: Perceived ease of use negatively influences privacy concerns	-.307	-.150	.157↓
H_9: Perceived usefulness negatively influences privacy concerns	.282	.259	.023↓
H_{10}: Subjective norms are related to privacy concerns	.067	-	Removed
H_{11}: Perceived behavioral control is related to privacy concerns	.283	.275	.008↓
Interactions			
$H_{1\text{-}1}$: The level of privacy concerns will moderate the positive relationship between attitudes and intentions	.172	.472	.300↑
$H_{2\text{-}1}$: The level of privacy concerns will moderate the positive relationship between subjective norms and intentions	-.044	-.046	.002↑
$H_{3\text{-}1}$: The level of privacy concerns will moderate the positive relationship between perceived behavioral control and intentions	-.036	-	Removed
$H_{4\text{-}1}$: The level of privacy concerns will moderate the positive relationship between perceived ease of use and intentions	.010	-	Removed
$H_{5\text{-}1}$: The level of privacy concerns will moderate the positive relationship between perceived usefulness and intentions	-.085	-.105	.020↑
Control Variable			
Effect on passengers' behavioral intentions while controlling for the other variables	.050	.050	No change
Effect on passengers' privacy concerns while controlling for the other variables	.109	.097	.012↓

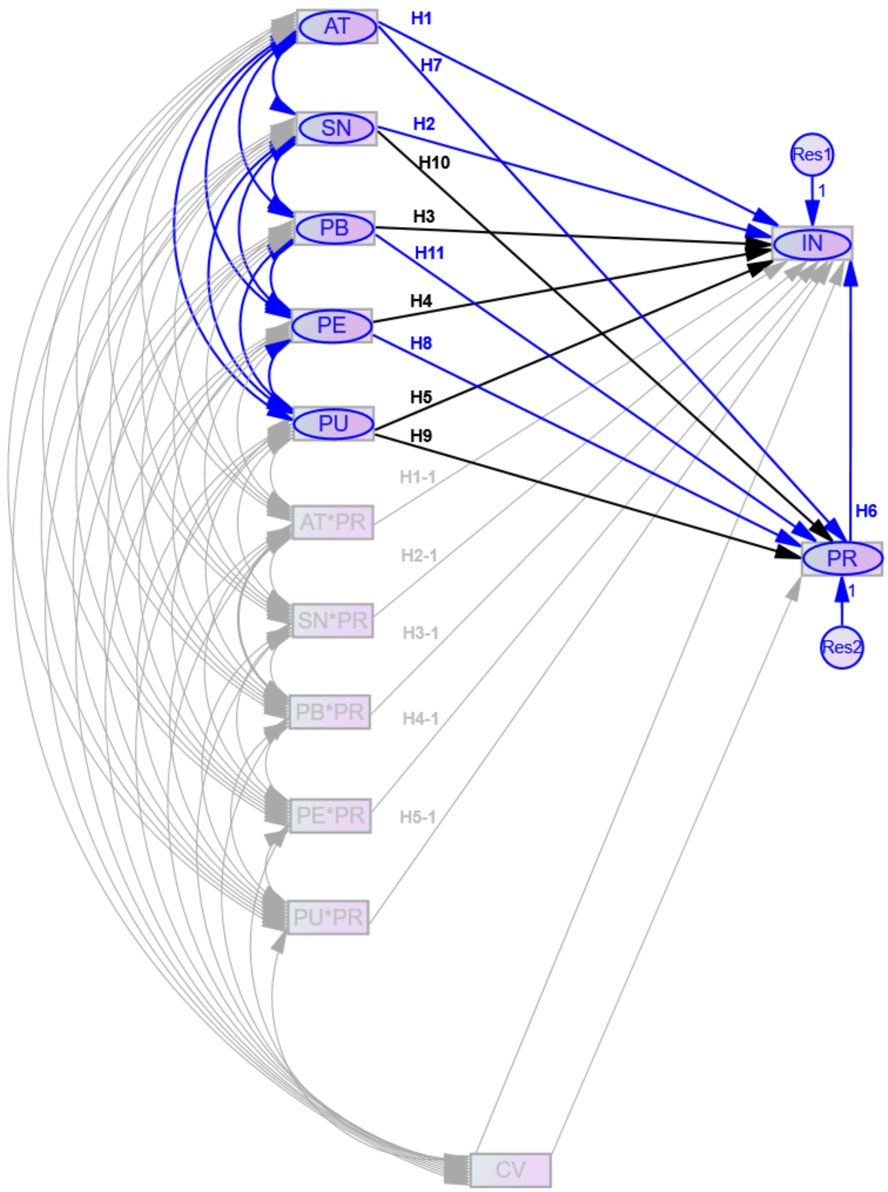
Note. ↑ = increase. ↓ = decrease.

Final SEM Model. A comparison of the initial SEM model and the modified SEM model shows there were no changes in the hypotheses that were supported across the three models. Furthermore, the same hypotheses were either removed or not supported when the initial and modified models were compared. An examination of the standardized regression weights from Table 31 also indicates that there are only slight changes from the two models with the interaction effects.

While three out of the five interaction effects hypothesized in the model were significant, they did not add to the predictive variance. Similarly, although the moderations were statistically significant, their effect sizes were small, and thus, while statistically significant, practically, they did not add much value to the model. Therefore, the initial SEM model without interaction effects was adopted as the final model. The final model superimposed over the model with the interaction effects is shown in Figure 16 with the hypotheses that were supported color coded in blue, while the hypotheses that were not supported are in black font.

Figure 16

Final SEM Model Superimposed on SEM Model (Interaction Effects), and Significant Paths Depicted in Blue



Note. AT = Attitudes; SN = Subjective Norms; PB = Perceived Behavioral Control; PE = Perceived Ease of Use; PU = Perceived Usefulness; CV = Coronavirus (COVID-19); PR = Privacy Concerns; IN = Intention to Use.

Chapter Summary

This chapter presented the results from the study. The initial face and content validity assessment that was conducted provided valuable comments which were then used to amend the questionnaire. Following the validity assessment, a pilot study was conducted to check the research procedures and provide an evaluation of the questionnaire. The completion of the pilot study resulted in further changes to the questionnaire, before a second pilot study was conducted. Finally, the main study was conducted with a sample size of 689 persons, more than the earlier determined minimum sample size of 500 persons. Both pilot studies and the main study were conducted using a sampling frame of participants from Amazon ® Mechanical Turk ®.

Demographic characteristics of respondents were summarized and showed that the survey respondents were younger, had a higher level of education, and a lower average income than the U.S. population. The MTurk sample had more male respondents, while the ethnic composition was fairly similar to that of the U.S. population. In terms of descriptive statistics, the mean, standard deviation (*SD*), kurtosis, and skewness were presented for the latent factors that were postulated to influence passengers' intentions to use biometrics. The moderating influence of privacy on the factors was also examined, while a COVID-19 variable was included to determine if there was any effect of COVID-19 (CV) on passengers' behavioral intentions and passengers' privacy concerns while controlling for the other variables.

The CFA measurement model of passengers' behavioral intentions showed an acceptable model fit but did not demonstrate acceptable reliability and construct validity, due mainly to poor factor loading of the PB2 item. Following a check of the literature, the item was removed from the model. The re-specified CFA model was used for the SEM process since it showed a slight improvement in model fit and showed acceptable reliability and construct validity.

The SEM model displayed model fit indices that were similar to the re-specified CFA model. The results of the hypotheses testing showed support for six of the hypotheses (H_1, H_2, H_6, H_7, H_8, H_{11}), while five (H_3, H_4, H_5, H_9, H_{10}) were not supported. The two hypotheses proposed for the control variable were also supported. There was no change in model fit results and hypotheses testing when the control variable was removed from the model suggesting that there was no significant effect of COVID -19 on passengers' behavioral intentions and passengers’ privacy while controlling for the other variables.

When the SEM model was reconfigured to include the interaction effects, the same six hypotheses as in the model without interaction effects were supported while the same five hypotheses were not supported. Three of the five hypotheses introduced for the interaction effects were supported (H_{1-1}, H_{2-1}, H_{5-1}) while two (H_{3-1}, H_{4-1}) were not supported. As with the model without interaction effects, the two hypotheses proposed for the control variable were also supported.

Further evaluation of the SEM model with interaction effects initially showed an unacceptable model fit. The model subsequently required several iterations during the post hoc analysis to obtain a satisfactory model fit. It was noticed, however, that the effect sizes of the interactions were small, and although statistically significant, the interactions did not add much value to the model. It was therefore decided to adopt the initial SEM model without interaction effects as the final model. The next chapter discusses these results further, provides conclusions from the present study, and suggests recommendations to guide future studies.

Chapter V: Discussion, Conclusions, and Recommendations

The current study examined the factors that influence passengers' intentions to use biometrics at airports. Additionally, the study also investigated the possible moderating influence of privacy. Specifically, the research focused on the intentions to use facial recognition technology to complete the required identification and verification process at an airport, while the moderating influence of passengers' privacy concerns on the factors was examined as part of the study. The study also included a coronavirus variable that was used as a control variable to assess the influence of the COVID-19 pandemic on passengers' behavioral intentions to use biometric technologies at airports due to the current and ongoing health crisis at the time of data collection.

The research model used for the study was developed following the review of the literature and was based on the grounded theory established by the theory of planned behavior (TPB). In addition to the factors of the TPB, perceived ease of use and perceived usefulness were included as additional factors that could influence passengers' intentions. Survey data for the study was collected with an electronic questionnaire developed using Google Forms ® and from a sample of participants selected via the Amazon ® Mechanical Turk ® platform. Thereafter, the data analysis for the main study was conducted using the methodology previously described while the previous chapter presented the results from the study. This chapter is the final chapter and presents a detailed discussion of the results, makes appropriate conclusions, and provides recommendations to stakeholders and to guide subsequent studies.

Discussion of Results

This section presents an examination of the findings detailed in the previous chapter against applicable theories and findings from other studies. First, the results from the demographic characteristics are reviewed. Next, this section presents a discussion of the SEM model results including an analysis of the influencing factors on the model. Finally, the section highlights any new findings and provides further understanding of some of the reasons that could explain the results.

Demographics. Demographic data collected from respondents during the study include age, gender, highest level of education attained, ethnicity, and annual income in United States Dollars (USD). Respondents were also requested to indicate if they had any prior use of facial recognition technology for the purpose of identification and verification at an airport. Due to the COVID-19 pandemic, an additional question was included to assess whether the pandemic had any perceived effect of COVID-19 on respondents' behavioral intentions.

As noted in the previous chapter, the results showed that the survey respondents were on average younger than the national U.S. population, an outcome that is consistent with previous studies with MTurk respondents (Berinsky et al., 2012; Heen et al., 2014; Huff & Tingley, 2015). Previous studies have also suggested that there is a negative relationship between increasing age and intention to adopt a new technology (Harris, Cox, Musgrove, & Ernstberger, 2016; Hwang, Lee, & Kim, 2019; Lian & Yen, 2014; Zhou, Rau, & Salvendy, 2014). Therefore, with 64.6% of the respondents in this study aged 39 years or less, it is not surprising that the overall view of the behavioral intention of the respondents toward biometric technologies was positive.

Regarding gender, the ratio of males (58.3%) to females (41.2%) among the respondents seen in this study is not the same as the U.S. population ratio of 49% male and 51% female (U.S. Census Bureau, 2019a). The ratio in this study is, however, similar to the gender ratio of 55% male and 45% female, when considering the characteristics of the MTurk worker pool available at the time of the study (Difallah et al., 2020). Although previous studies on the gender differences in technology adoption appear to be inconclusive on the role of gender in the adoption of new technologies, there is an acknowledgement that gender plays an important moderating role in adopting new technology (Hwang et al., 2019).

Some studies found that males were more likely to adopt new technology (Chen, Yan, Fan, & Gordon, 2015; Ong & Lai, 2006; Van Slyke, Comunale, & Belanger, 2002). Other studies suggested that females were the ones more likely to adopt new technology (González-Gómez, Guardiola, Rodríguez, & Alonso, 2012; Joiner et al., 2012; Venkatesh et al., 2003). Although this relationship was not fully examined in this present study, it is probable that the higher percentage of male respondents in this study suggests a more positive outlook on the behavioral intentions of males toward the adoption of technology.

The results from the study for the highest level of education obtained by respondents did not permit a direct comparison of the subgroups to equivalent U.S. national data. However, the results suggest that the MTurk respondents had a higher level of education when compared to the U.S. population. This is also consistent with studies that have shown that MTurk samples are generally more educated than samples drawn from national probability samples (Berinsky et al., 2012; Chandler, Rosenzweig, Moss, Robinson, & Litman, 2019; Huff & Tingley, 2015; Levay, Freese, & Druckman, 2016; Michel, O'Neill, Hartman, & Lorys, 2018).

Regarding ethnicity, the survey respondents were found to mostly belong to the 'White or Caucasian' subgroup (76.8%); there was no other subgroup with more than 10% of respondents. While there were some differences within the subgroups, overall, the MTurk sample was found to be a fair ethnic representation of the U.S. population. This result is in line with findings from previous studies that have found MTurk samples to contain lower percentages of non-white groups, but otherwise in general are closely representative of the U.S. population (Berinsky et al., 2012; Burnham, Le, & Piedmont, 2018; Huff & Tingley, 2015; Levay et al., 2016; Paolacci & Chandler, 2014).

The median income of the survey respondents at $50,000, when compared to the reported median income for the U.S. population of $63,179 (U.S. Census Bureau, 2019b), suggests that the MTurk sample had a lower income level than the U.S. population. This result also supports findings from prior studies that MTurk samples tend to have lower average incomes when compared to the U.S. population (Berinsky et al., 2012; Difallah et al., 2018; Garrow et al., 2020; Huff & Tingley, 2015; Levay et al., 2016; Paolacci & Chandler, 2014).

The majority of respondents that answered the question about their prior use of facial recognition technology at an airport (79.8%) reported they had no prior use of the technology. Since the technology is not yet widely available at all airports, it may not be possible to compare this with the general population. As noted in Chapter 1, the U.S. Customs and Border Protection (CBP) working with its partners, select airlines, and airports, has introduced the Traveler Verification Service (TVS) to support immigration entry and exit at 22 airports in the U.S. It is expected that more people will have the opportunity to experience the technology as the service expands to more locations.

Regarding the effect of the COVID-19 crisis, the majority (81%) of respondents did not expect that the crisis would have an effect on their perception of intention to use biometrics at airports. This result appears to indicate that while respondents are well aware of the current pandemic and the attendant disruptions, it is still considered a temporary event that will eventually subside. Biometrics, on the other hand, appear to be considered a useful technology with longer term benefits. Indeed, one of the lasting effects of the pandemic could be the increase and wider acceptance of various touch-free technologies. As summarized in the previous chapter, overall there were more positive than neutral or negative additional comments about the survey or about biometrics in general from the respondents. It is also interesting that the touch-free nature of the specific facial recognition technology was recognized and applauded, as seen in some of the comments.

Model Results. The model used in this study comprised five exogenous variables: attitudes, subjective norms, perceived behavioral control (PBC), perceived ease of use, and perceived usefulness. Intention to use biometric technologies at airports was the endogenous variable, while privacy was studied as a moderating variable on the other variables. A coronavirus (COVID-19) scale was also included in the model as a control variable and was treated like one of the exogenous variables that could influence passengers' behavioral intentions to use biometric technologies at airports.

There were 11 hypotheses in the initial model without interaction effects. Six of the hypotheses were supported (H_1, H_2, H_6, H_7, H_8, H_{11}), while five hypotheses (H_3, H_4,

H_5, H_9, H_{10}) were not supported. When the interaction effects were included in the model, three of the five hypotheses introduced were supported ($H_{1\text{-}1}$, $H_{2\text{-}1}$, $H_{5\text{-}1}$) while two hypotheses ($H_{3\text{-}1}$, $H_{4\text{-}1}$) were not supported. The two hypotheses proposed for the control variable were also supported with both models. The relationships are discussed in detail in the following paragraphs.

Attitudes. In the context of this study, attitude refers to an individual's positive or negative feeling toward the use of biometrics at airports. This study found that passengers' attitudes positively influenced passengers' intentions to use biometric technologies at airports. This finding was expected as the relationship is one of the fundamental relationships of the TPB, as postulated by Ajzen (1991, 2005). Other studies have also used the TPB to confirm a positive and significant relationship between attitudes and intentions (Garrison, Rebman, & Kim, 2018; Hua & Wang, 2019; Jin Ma, Littrell, & Niehm, 2012; Liu, Smith, & Gallois, 2013; Reza Jalilvand, & Samiei, 2012). Specifically, consumers have been shown to display positive attitudes toward the use of biometrics (Morosan, 2012a, 2012b; Riley, Benyon, Johnson, & Buckner, 2010; Seyal & Turner, 2013). The positive attitudes by respondents in this study could be explained by the perceived benefits from biometrics such as increased convenience, faster and easier boarding, and improved security. The results from this study indicate that passengers with positive attitudes toward biometrics are more likely to use biometrics at airports than passengers with neutral or negative attitudes.

Another direct relationship considered the influence of attitudes on passengers' privacy concerns with the use of biometrics. The hypothesized negative relationship in this study was supported implying that an increase in privacy concerns with the use of biometrics will lead to a decrease in passengers' attitudes toward the use of biometrics and vice versa. This result is aligned with studies that found a significant negative relationship between perceptions of privacy and attitudes (Carpenter et al., 2018; Joinson et al., 2006; Miltgen et al., 2013). However, it is noted that there are other studies that have found that the relationship between privacy and attitudes was either positive, or the negative relationship was not significant (Merlano, 2016; Morosan, 2012b; Neo et al., 2016).

The negative relationship found in this study was also confirmed from the review of additional comments provided by some of the respondents where they highlighted their privacy concerns with the use of biometrics. It appears that while passengers generally accepted the benefits of using biometrics, there were privacy concerns with the use or potential misuse of their personal data. Furthermore, even though the study considers voluntary use of biometrics by passengers, there was a perception, also confirmed from the additional comments, that the airport setting could create a feeling that the data or information provided would eventually be obtained by government agencies without their consent.

Finally, this study also examined the positive relationship found between passengers' attitudes and intentions to use biometric technologies to determine whether privacy concerns had a moderating influence on the relationship. It was found that privacy concerns strengthen the positive relationship between passengers' attitudes and intentions. The results, as seen in Chapter IV, also show that low privacy concerns have a stronger effect on the attitudes-intentions relationship than high privacy concerns. The implication is that passengers with low privacy concerns toward biometrics are more affected by the attitudes-intentions relationship than passengers with high privacy concerns. However, as passengers' privacy concerns increase, the effects reduce such that at some point the effect of the attitudes-intentions relationship becomes stronger when passengers have higher privacy concerns.

This finding appears to support prior research that investigated the term known as the 'privacy paradox', which focuses on individuals that have concerns about their privacy but are still willing to share their personal information because of what they believe they will gain in return (Büschel, Mehdi, Cammilleri, Marzouki, & Elger, 2014; Ioannou, Tussyadiah, & Lu, 2020; Kokolakis, 2017; Norberg, Horne, & Horne, 2007). The finding in this study could thus be explained that while passengers are concerned about privacy, the perceived benefits, as previously mentioned, mean they were still likely to want to make use of biometric technology. Furthermore, given recent world developments related to the COVID-19 pandemic, the contactless nature of the transactions may have created additional perceived benefits.

Subjective Norms. Subjective norms refer to an individual's belief that people who are important to the individual would approve of a particular course of action. In this study, subjective norms relate to a person's perception of the social pressure from people important to the person, such as friends and close relations, toward the decision to use biometrics at airports. The results showed that subjective norms had a positive influence on intentions, a relationship that is also supported by the TPB. The finding is also consistent with various studies that affirmed the significant influence of subjective norms on an individual's intention to perform a specific behavior (Kim & Bernhard, 2014; Liao et al., 2007; Seyal & Turner, 2013; Tsai, 2010). In this study, the result probably indicates that respondents believe a decision to use biometrics would be supported by their friends and families once they hear about it. It is possible that the thought of telling others about the use of a novel technology already weighs on their mind and influences the decision to use biometrics. Generally, people love to tell others about their travel experiences, so a successful outcome with the use of biometrics would likely be a significant part of the overall travel experience that would be shared with others.

A non-directional hypothesis was also proposed to examine the relationship between subjective norms and privacy concerns. This relationship was not supported suggesting that passengers do not consider the opinions from people close to them to be important in privacy concerns with the use of biometric technologies. The lack of support for the hypothesis as framed in this study could mean that the logic of the hypothesis should be reassessed, taking the theory and further literature review into consideration. For example, the study by Riley et al. (2009), which surveyed differences in privacy concerns across cultures, found that Indian respondents rated privacy concerns with biometrics less of a problem than United Kingdom respondents. While there was no direct study with U.S. respondents, a comparison could be made using the dimensions of national culture as defined by Hofstede (1983). Per Hofstede Insights (n.d.), the Individualism-Collectivism dimension (which measures the degree of interdependence among people) ranks India at 48 (intermediate - both collectivistic and individualist traits), and the United Kingdom at 89 (highly individualist). With the U.S. ranked at 91 (highly individualist), it could be inferred that people from highly individualist countries such as the U.S would rate privacy concerns with biometrics high and not necessarily consider the opinions of people close to them in making the decision.

The final relationship with subjective norms in this study examined the moderating effect of privacy concerns on the relationship between subjective norms and intentions. Results indicated that the moderating variable had a significant effect. In this case, privacy concerns were found to dampen the positive relationship between subjective norms and intentions. This result could be compared with the previously mentioned research that involved the direct effects of subjective norms on intentions to use biometrics (Kim & Bernhard, 2014; Seyal & Turner, 2013) and the direct effect of privacy concerns on intentions (Kim & Bernhard, 2014; Miltgen et al., 2013). With the result in this study, it appears that respondents do not feel that the opinions of most people important to them would matter when the respondents have privacy concerns on intentions to use biometrics.

Perceived Behavioral Control. Perceived behavioral control (PBC) is the perception of an individual of the ease or difficulty of performing a specific behavior (Ajzen, 1991). This study considered the perceived control of an individual in making the decision to use biometrics. The hypothesized relationship was not supported indicating that PBC did not significantly predict passengers' intentions as they relate to the use of biometrics. Although the finding is against the expected relationship in the TPB, there are various studies that have also found PBC to be an insignificant predictor of intention (Halder, Pietarinen, Havu-Nuutinen, Pöllänen, & Pelkonen, 2016; Jing & Juan, 2013; Moons & De Pelsmacker, 2015; Pan & Truong, 2018; Soon & Wallace, 2017).

The finding in this study is interesting as it suggests that passengers' requirement for their perceived control in making the decision to use biometrics is considered low. It is possible that because of the voluntary nature of the study, respondents feel that they have full control of the decision to use biometrics and therefore have little consideration for perceived control. It is also possible that respondents felt that since the decision to use biometrics is already an indication of having exercised their full control, perceived control would no longer be an important factor.

Another hypothesis with PBC examined the relationship between PBC and privacy concerns. The relationship was found to be positive and significant suggesting that an increase in the control that a passenger perceives over the decision to use biometrics will lead to an increase in privacy concerns. This relationship appears to be in line with previous studies that found an increase in PBC would lead to an increased tendency to protect information privacy (Ma et al., 2016; Tabak & Ozon, 2004). However, the result is inconsistent when compared with studies which suggested that users with increased perceived control over the use and collection of their personal information tend to report lower privacy concerns (Culnan & Armstrong, 1999; Nowak & Phelps, 1997; Sheehan & Hoy, 2000; Xu, 2007). In the context of this study, the divergent result provides a useful insight for a consideration of a directional hypothesis, rather than the non-directional hypothesis used in this study. It is also possible that passengers did not associate PBC (defined as the perceived control of making the decision to use biometrics) in this study with an effect on their privacy.

The hypothesis to examine how the level of privacy concerns moderates the relationship between PBC and intentions was also not supported. The result could suggest that there is a negative relationship between PBC and intention, rather than the positive relationship that was hypothesized in the study. This result of this hypothesis is not considered surprising since there was no support for the direct relationship between PBC and intentions, as has been discussed above.

Perceived Ease of Use. Perceived ease of use is a key variable of the technology acceptance model (TAM) and in this study, measured the degree to which a passenger believes that using biometrics at airports would be completed without any significant exertions. The hypothesized relationship between perceived ease of use and passengers' intentions was not supported, suggesting that passengers did not consider perceived ease of use to be an important factor in the intention to use biometrics. This finding is against the relationship of the TAM which suggests that perceived ease of use through the attitude toward use influences how users accept and use a new technology. However, other studies have also found that perceived ease of use is not a significant determinant of usage intention (Hussein, 2017; Mohammed, 2018; Mohd Suki, & Mohd Suki, 2017; Pikkarainen, Pikkarainen, Karjaluoto, & Pahnila, 2004; Wu & Wang, 2005).

It is possible that this result was influenced by the specific type of biometric device adopted in this study. A different type of biometric device may be perceived in another manner by respondents. This possibility is addressed in the section on suggested areas for further research. The insignificant results could also be explained from the choice of the sample of this study. First, with majority of respondents (79.8%) reporting they had no prior use of facial recognition technology at airports, it is possible that the general awareness of biometrics from other devices such as smartphones may have created a perception that the use of facial recognition technology would not be any more difficult than what they would be normally used to. Second, it is also possible that with 64.6% of the respondents aged 39 years and below, the majority of them could already be technologically-savvy, and therefore did not expect that ease of use could be a factor in their decision to use biometrics. Further study could also consider a different sample.

This study further examined perceived ease of use in relation to privacy concerns. In this case, the negative hypothesis was supported which suggests that increased passengers' perceived ease of use of biometrics will result in reductions in passengers' privacy concerns. The finding is similar to the finding from the study by Oh et al. (2019) that assessed perceived ease of use as a factor of usability and found that reduced privacy concerns would improve the usability of a system. The hypothesis that examined the moderating effect of privacy on the relationship between perceived ease of use and intentions was also not supported. Although the relationship was found to be positive, it was not significant.

Perceived Usefulness. Perceived usefulness is also a key variable of the TAM and in this study was described as the extent to which a passenger believes that using biometrics at airports would be advantageous for them. Similar to the outcome with perceived ease of use, the hypothesized positive relationship between perceived usefulness and passengers' intentions was also not supported, possibly reflecting the close relationship between the two key TAM constructs. While the TAM has gained notable prominence in explaining the relationship between use of technology and behavioral intentions, a few studies have found only a limited or insignificant effect of perceived usefulness on behavioral intentions (Kasilingam, 2020; Teo & Milutinovic, 2015; Wang, Lew, Lau, & Leow, 2019; Wong, 2016).

In the context of this study, the results suggest there are other factors that passengers consider more important than perceived ease of use and perceived usefulness when there is a decision regarding the use of biometrics. Morosan (2012b, 2018) identified some of the other factors to include trust, anxiety, and negative or positive emotions. One possible reason for the result could be that respondents would want to balance the usefulness of the system with concerns about the safety of their biometric data. A review of some of the additional comments provided by respondents in the study allude to the concerns. The lack of support for the usefulness – intentions relationship in this study could also imply that respondents do not believe that completing the airport processes using biometrics is superior to the traditional manner that they were already used to and would therefore choose to maintain the use of the traditional processes.

Another hypothesis with perceived usefulness examined the relationship of perceived usefulness to privacy concerns with the use of biometrics. The result showed that the negatively hypothesized relationship suggested in the study was not supported. There is some evidence that users' concerns about privacy influence their views of biometric systems (Morosan, 2012b; Sasse, 2005). Therefore, it is possible that the relationship between perceived usefulness and privacy concerns is a positive one such that when passengers perceive a more favorable usefulness for biometrics, their privacy concerns toward the use of biometrics are increased. The novelty of the technology and the fact that most respondents had not used the technology may have led to this result. The result could also be explained within the context of the lack of support for the usefulness – intentions relationship earlier discussed such that respondents may have been biased by their perception of intentions in this response regarding privacy concerns.

The final hypothesis involving perceived usefulness examined the moderating effect of privacy concerns on the positive relationship between perceived usefulness and intentions. This hypothesis was supported with privacy concerns found to dampen the positive relationship between perceived usefulness and intentions. This weakening relationship should be compared with the direct effect of privacy concerns on intentions to use biometrics (Kim & Bernhard, 2014; Wang et al., 2006; Zhou, 2012) and with the direct effect of perceived usefulness on intentions (Davis et al., 1989; Jackson et al., 1997; Legris et al., 2003; Lu et al., 2009). While the result appears to confirm the positive relationship between perceived usefulness and intentions, there is a further implication that passengers do not feel that the perceived usefulness of biometrics will be considered to be an important factor when they have privacy concerns with the use of biometrics.

Control Variable. Due to the global pandemic ongoing at the time of the study, coronavirus disease (COVID-19) was introduced in the model as a control variable that could influence passengers' behavioral intentions and privacy concerns (the endogenous variables) with the use of biometric technologies at airports. As explained in Chapter IV, the results from the hypotheses suggest there was no significant effect of COVID-19 on passengers' behavioral intentions and passengers' privacy concerns while controlling for the exogenous variables. The implication of this finding appears to be that passengers did not consider COVID-19 to be significant in their decision regarding the use of biometrics. The additional comments provided by respondents also corroborated this with nearly half of all comments on COVID-19 being adjudged to be positive comments.

There is research that shows individuals make changes in travel behaviors in response to epidemics or pandemics (Bayham, Kuminoff, Gunn, & Fenichel, 2015; Fenichel, Kuminoff, & Chowell, 2013; Kim, Cheon, Choi, Joh, & Lee, 2017). Other studies also show that responses to a pandemic were based on theories of risk perception.

A greater perception of risk could lead to fatalism and avoidance, while a lower perception of risk could lead to underestimation (Bults et al., 2011; Kok et al., 2010). Considering when the current study took place, it is possible that the comments and the responses provided are a reflection of the early to mid-outbreak stage of the pandemic and an overall low perception of risk by respondents. Furthermore, it is also plausible that any effect of COVID-19 was considered temporary while the overall long-term view of biometrics was positive, therefore, other factors were considered more important in the decision to use biometrics.

Conclusions

This research studied the factors that influence passengers' behavioral intentions to use biometrics at airports. In addition to examining the moderating effects of privacy concerns on the relationships between the factors and intentions, the study also examined the direct relationships between privacy concerns and the factors. The theoretical model for the study was based on the TPB, while perceived ease of use and perceived usefulness were included as additional factors that could influence behavioral intentions. Due to the pandemic at the time of the study, a coronavirus (COVID-19) scale was introduced as a control variable to examine the effects of COVID-19 on passengers' behavioral intentions while controlling for the other variables.

A review of the results presented in Chapter IV and the discussions in the preceding sections in this Chapter indicate that only two factors, attitudes and subjective norms influenced passengers' intentions. Significant relationships were also found between privacy concerns and four of the factors, namely behavioral intentions, attitudes, perceived ease of use, and perceived behavioral control. Regarding the moderating effects, privacy concerns were found to moderate the relationships between intentions and three of the factors: attitudes, subjective norms, and perceived usefulness. However, the effects were not considered to be of much value, hence the final model did not include the moderations. Finally, there was no significant effect of the control variable (COVID-19) on passengers' behavioral intentions and passengers' privacy concerns while controlling for the other variables.

The current study proffered a model for passengers' behavioral intentions to use biometrics at airports. With the additional focus on the moderating effects of privacy concerns and the inclusion of a control variable, this study provides valuable contributions. The next section presents the contributions in detail.

Theoretical Contributions. This study makes four important contributions to the literature. First, the study extends the use of the theory of planned behavior (TPB) to explain passengers' behavioral intentions to use biometrics at airports. The study added perceived usefulness and perceived ease of use (factors of the TAM) to factors of the TPB and used SEM techniques to analyze the data. This approach allowed a greater examination of passengers' intentions than previous studies on the use of biometrics. Some of the prior studies either used the TAM with additional factors, (Miltgen et al., 2013; Morosan, 2012a) or omitted other factors that could affect behavioral intentions in the model (Seyal & Turner, 2013). The results of this study showed the final model as more dependent on the TPB factors than the TAM factors, and can also be considered a major contribution to the literature.

Second, the study adds to the overall understanding of the factors influencing the voluntary use of biometrics at airports and makes a significant contribution with the examination of the moderating effects of privacy concerns on behavioral intentions. This study assessed the influence of privacy concerns on the relationships between passengers' behavioral intentions and the following factors: attitudes, subjective norms, perceived behavioral control, perceived ease of use, and perceived usefulness.

While there are few studies that considered the moderating effects of privacy on relationships involving intentions (Liang & Shiau, 2018; Yun, Han, & Lee, 2013), this study appears to be one of the first studies to examine the moderating effects of passengers' privacy concerns on relationships with behavioral intentions to use biometrics. Furthermore, though the final model did not include the moderated relationships, the identification of privacy concerns as a moderator in three of the relationships contributes to the literature on moderations and on behavioral intentions.

Third, this study contributed to the literature with the investigation of the effect of COVID-19 on passengers' behavioral intentions and passengers' privacy concerns while controlling for the other variables. Because the timing of the study meant that there was a possibility that the COVID-19 pandemic could have an effect on passengers' behavioral intentions, COVID-19 was included as a control variable to ensure its effect could be balanced while studying the relationships between the exogenous and the endogenous variables. The method used to evaluate the effects is supported by the literature (Aguinis & Vandenberg, 2014; Becker, 2005; Bernerth & Aguinis, 2016) and involved comparing the results of the model analyses with and without COVID-19. As the results were not significantly different, COVID-19 could therefore be excluded as a potential explanation for the findings from the study. In addition, since the comparison between the hypothesis tests did not yield significant differences, COVID-19 was removed from the final model.

Fourth, the demographic data from the study provides a contribution on the characteristics of the different demographic groupings as they relate to intention to use. While the influence of demographics on intentions was not directly observed in this study, the MTurk sample provided valuable information regarding the behavioral intentions of this sample data set.

Practical Implications. The measures taken by the researcher during the present study, including the face and content validity assessment, and the two pilot studies helped to improve the study's generalizability, reliability, and validity. Hence, the findings can provide practical implications for all stakeholders involved with assessing passengers' behavioral intentions regarding the use of biometrics. Three practical implications are discussed in this section.

The first implication follows from the finding of the study that attitudes and subjective norms significantly influence passengers' intentions to use biometric technologies at airports, with attitudes being the stronger predictor of intentions. Accordingly, airport operators should endeavor to make passengers have positive feelings and experiences about using biometrics. Furthermore, since subjective norms are also a significant predictor of intentions, passengers are likely to consider the opinions of persons close to them in the decision to use biometrics. In this case, the shared experiences of passengers will have practical implications on the behavioral intentions and ultimately on actual use of biometrics.

The second practical implication concerns the relationships between privacy concerns and the factors behavioral intentions, attitudes, perceived ease of use, and perceived behavioral control. As the relationships were significant, it is important for biometric systems to be designed with considerations given to users' privacy concerns. Passengers should also be given the option to decline the use of biometrics at any time and should have the assurance that their data would be treated securely. Consequently, biometrics system owners and operators usually provide privacy policy agreements or statements outlining passengers' rights and provide means for passengers to seek redress for rights violations. Although the strengths of the moderating effects of privacy concerns were adjudged to be low, the effects are also likely to result in some implications for behavioral intentions in the use of biometrics.

The third practical implication arises due to the assessment of the effect of COVID-19 on passengers' behavioral intentions and passengers' privacy concerns while controlling for other variables. As the effect in the current study was not significant, the implication is that COVID-19 was not considered to be associated with behavioral intentions or with passengers' privacy concerns. Furthermore, the result also allowed COVID-19 to be ruled out as an alternative explanation for the results from the study.

While the impact of COVID-19 on passenger travel and the overall world economy has been major, this finding has an important implication for airport operators and other biometric systems providers in the continuous use and expansion of biometric systems. For example, Airports Council International (ACI) and IATA, in their joint report on restarting aviation after COVID-19 stated that a greater use of biometrics in check-in and boarding should be pursued as part of measures to limit contact at passenger's touch points (ACI & IATA, 2020).

Limitations of the Study. This section identifies four limitations of the current study. First, because of the nature of the sampling frame selected for the study, the results may not be generalizable beyond those persons who complete online human intelligence tasks. However, this study identified several studies that confirmed MTurk participants are fairly representative of the U.S. population and can thus provide reliable data (Berinsky et al., 2012; Buhrmester et al., 2011; Paolacci et al., 2010). Furthermore, the study could be applied to other sample groups within the target population using the same methodology.

Second, there is a limitation of the survey as it concerns the time the survey was conducted. Since a survey samples opinions of respondents at a specific time, these opinions are therefore dependent on the conditions that may be occurring at that time. In this regard, the possible effect of the coronavirus pandemic (COVID-19) occurring at the time of the study has already been considered with its inclusion as a control variable. While the results may not be generalizable over a different time period, the study could be replicated at different times to verify the results from this study.

Third, another limitation of surveys relates to the nature of surveys that requires respondents to limit their opinions to specific categories. To mitigate this, the design in this study allowed respondents the option to provide comments with their survey. The additional comments provided by respondents were especially useful in the overall assessment of passengers' intentions.

Fourth, a limitation may result from the scope of the study which limited the choice of additional factors included with the TPB factors in the model. While perceived usefulness and perceived ease of use were included as additional factors, it is possible that there are other factors that could influence passengers' intentions to use biometrics at airports. The inclusion of privacy concerns in the study and the examination of its moderating effects on the factors partially helped to address this limitation.

Recommendations

From the discussions of the results and the conclusions presented in this Chapter, this study proposed recommendations under two main subheadings – recommendations for stakeholders and recommendations for further research.

Recommendations for Stakeholders. This study provides some recommendations for stakeholders such as airport operators and owners, governments, airlines, and biometric technology providers that are involved in the production and use of biometrics systems and applications.

Airport operators and owners should give priority to the continuous installation and operation of passenger-friendly and easy-to-use biometrics systems. Where such systems are already installed, consideration should be given to the additional systems support and upgrades to ensure passengers can have access to the most recent technologies. This is important as this study found that passengers are likely to use biometric systems if they show positive attitudes toward the systems and are also likely to be motivated by the opinions of people close to them in the decision to use biometrics. In addition, the expected increase in worldwide passenger air traffic and the reductions in passenger handling times at airports where biometrics have been used make this an attractive proposition to consider.

While this study did not consider the mandatory use of biometrics as required by government agencies, the findings provide important recommendations particularly in the area of passengers' privacy concerns with the use of their data. It is recommended that passengers should be given all information regarding the use of any data they provide to a biometric system. Furthermore, the data provided should be utilized specifically for the purpose of identification and verification of the passenger at the specific time. As soon as this process is concluded, the data should be destroyed or made inaccessible to any other user without the permission of the passenger. This should be the minimum that any passenger should expect, and this fact should be clearly known to the passenger.

The collaboration between airlines and airports in the installation and use of biometric systems and applications also needs to continue to ensure the overall transformation of the passenger experience is sustained. For example, British Airways reported that the use of facial recognition at some airports enabled the airline to halve the time of the boarding process such that they achieved an average boarding rate of about 18 passengers per minute (ACI & IATA, 2020). Further integration of airline and airport systems with mobile devices and apps should also be pursued to manage passenger identification via a single identifier.

Biometric technology systems providers are in the forefront of the development of innovative biometric products. It is expected that companies and other organizations focused on consumer research will allocate the required resources to the research and development of facial recognition technologies. The market for facial biometrics is projected to surpass $15 billion by 2027, and it is expected that passenger use at airports will contribute significantly to that amount (Biometricupdate, 2020). This creates opportunities for companies to develop novel products to enhance the passenger experience at airports. Some of the areas for growth include 3D facial recognition, thermal facial recognition, cloud-based facial recognition services, training and consulting services, and emotion recognition.

Recommendations for Further Research. This study provided the following recommendations to guide future research into passengers' intentions toward the use of biometrics.

First, the item PB2 ("The choice to use biometrics at airports is entirely up to me") was deleted from the CFA model due to unacceptable values for reliability and validity measures. Further research is suggested to investigate the reasons for this. Future research on passengers' intentions using the TPB could also consider a rewording of this item to determine if similar results would be obtained.

Second, further research is suggested to investigate the unsupported relationships in this study. These relationships, which involved perceived behavioral control, perceived ease of use, and perceived usefulness to intentions and the relationships of perceived usefulness and subjective norms to privacy concerns should be further examined and possible alternative explanations provided. Specifically, subjective norms could be examined in relation to privacy concerns using the dimensions of national culture as defined by Hofstede (1983) to determine the effects of cultural differences on passengers' behavioral intentions. Additionally, since the hypothesized negative relationship between perceived usefulness and privacy concerns with the use of biometrics was significant but in the wrong direction, further research could focus on this relationship. A future study for example could propose a positive relationship, and the result should also be considered together with the relationship between perceived usefulness and intentions to use as part of the model.

Third, additional research is recommended into attempts to boost the model's predictive power. While the predictive power explained by the factors used to predict intentions was considered strong at .802, there is a scope to determine other factors that could be combined to improve the model. Further study is also required to examine the effect of the combination of the TPB and TAM factors on the predictive power and to determine if the addition of external variables could add to the predictive power of the model. External variables that could be considered in line with the TAM framework of Davis et al. (1989) include system features, design characteristics, and availability of support personnel. The results from the current study suggested there are other factors that passengers consider important in the decision to use biometrics. Examples of these factors could include trust in the technology, perceived risk of the technology, anxiety, and emotions.

Fourth, future research should consider the relationship between passengers' behavioral intentions and actual behaviors toward biometrics. Although actual behavior is part of the TPB, and the available literature supports the notion that actual behaviors can be predicted from intentions (Ajzen, 1985, 2005; Madden et al., 1992), this relationship was not examined in this study.

Fifth, this research should be extended to a different sampling frame within the target population and to different populations outside the U.S. While the Amazon ® Mechanical Turk ® (MTurk) sample provided valuable information, it is important to study additional samples to determine if the results can be extrapolated to other groups.

Finally, as this study focused on facial recognition technology as the specific type of biometric technology, future study could examine passengers' intentions to use biometrics from the context of other biometric systems. It will be interesting to determine if there would be any significant differences in passengers' intentions with the use of other types of biometric technologies such as fingerprints, palms, voice, iris scan, and gait. In addition, future research should also include the study of more recent advances in biometric technology such as passive biometrics and behavioral analytics, machine learning and artificial intelligence, and Internet of things.

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Appendix A

Permission to Conduct Research

IRB Approval

EMBRY-RIDDLE
Aeronautical University
FLORIDA | ARIZONA | WORLDWIDE

11 May 2020

Modification of Previously Approved IRB

Campus:	**Worldwide**	College:	**COA**
Applicant:	**Kabir Kasim**	Degree Level:	**Doctorate**
ERAU ID:	**2402802**	ERAU Affiliation:	**Student**
IRB Approval Number:	**20-085**		
Project Title:	**An investigation of factors that influence passengers' intentions to use biometric technologies at airports**		
Principal Investigator:	**Kabir O. Kasim**		
Other Investigators:	**Dr. Scott R. Winter**		

Approval of Modification of Already Approved IRB:

☒ Validated as continuing to meet the criteria for Exempt or Expedited status.

Michael E. Wiggins, Ed.D — Signature of IRB Chair

May 14, 2020 — Modification Approval Date

Submission Date: **05/11/2020**

Beginning Date: **05/19/2020**

Type of Funding Support (if any):

Questions:

1. Change of Protocol due to change in:

   Data collection tools/procedures

1b. Please summarize:

   Due to the current coronavirus (COVID-19) pandemic, it is proposed to include a control variable to help account for any influence from the possible confounding variable on passengers' behavioral intentions to use biometric technologies at airports. The survey instrument has been modified to include a Perceived Coronavirus Threat Scale and an additional open-ended question on the perceived effect of the coronavirus on behavioral intentions. There are no other changes to any other aspects of the study.

2. Have you started the recruitment process?

   No

3. Have you received any complaints or experienced unanticipated problems with this project?

   No

EMBRY-RIDDLE
Aeronautical University
FLORIDA | ARIZONA | WORLDWIDE

12 February 2020

Human Subject Protocol Application

Campus:	**Worldwide**	College:	**COA**
Applicant:	**Kabir Kasim**	Degree Level:	**Doctorate**
ERAU ID:		ERAU Affiliation:	**Student**

Project Title: **An investigation of factors that influence passengers' intentions to use biometric technologies at airports**

Principal Investigator: **Kabir O. Kasim**

Other Investigators: **Dr Scott R. Winter**

Submission Date: **10/09/2019**

Beginning Date: **03/01/2020**

Type of Project: **Survey**

Type of Funding Support (if any):

Questions:

1. Background and Purpose: Briefly describe the background and purpose of the research.

   Biometric technologies, or more simply biometrics, involve the use of characteristics and measurements from humans to establish or verify their identity. The basic premise of biometrics relates to the use of computers and machines to provide verification and/or identification based on a person's unique physiological and behavioral characteristics. The purpose of this research will be to examine the factors that influence passengers' behavioral intentions to use biometric technologies at airports.

2. Time: Approximately how much time will be required of each participant?

   It is anticipated that it will take approximately 10 minutes for a participant to complete the survey.

3. Design, Procedures and Methods: Describe the details of the procedure(s) to be used and the type of data that will be collected.

The study will utilize a survey research design. A survey instrument will be uploaded to Google Forms while the participants will be recruited via the Amazon ® Mechanical Turk ® (MTurk) platform. Participants must be 18 years old and above and be registered as an MTurk worker in the United States. Participants will be presented with the online survey via a link in the MTurk posting, sign the consent form, then proceed to complete the survey. The survey will request responses regarding behavioral intentions to use biometrics. In addition, general demographic data including age (in years), gender (male or female), and the highest level of education attained (high school, bachelor's, master's, or doctorate) will be collected from participants. Other demographic data that will be collected include ethnicity and annual total income. There will be no personal identifying data that will be collected.

4. Measures and Observations: What measures or observations will be taken in the study?

The study will measure the opinions of participants based on the variables in the study. Participants will thus be required to select their responses to the question items on the Theory of Planned Behavior (TPB) constructs of attitudes, subjective norms, and Perceived Behavioral Control (PBC). Perceived ease of use and perceived usefulness are also included as variables to examine attitudes and intentions, while the study will also observe the moderating influence of passengers' privacy concerns on the factors that affect passengers' behavioral intentions. The variables will be measured using validated scales. The survey instrument is attached.

4b. If any questionnaires, tests, or other instruments are used, provide a brief description.

The questionnaire will be developed using Google Forms ® from existing instruments, and presented electronically to participants via the Amazon ® Mechanical Turk ® system (MTurk) hosting platform. Participants will be required to select their responses to the variables on 5-point Likert-type scales with endpoints and scores ranging from "strongly disagree" (-2) to "strongly agree" (+2). Multiple statements from each construct will be combined into a single composite score (the average) per construct during the data analysis process, assuming the Cronbach's Alpha of these statements is high. A copy of the questionnaire is attached.

5. Participant Population and Recruitment Procedures: Who will be recruited to be participants and how will they be recruited. Any recruitment email, flyer or document(s) must be reviewed by the IRB. Note that except for anonymous surveys, participants must be at least 18 years of age to participate.

The participant population will consist of those persons that are willing and are available to complete human intelligence tasks (HITs) from Amazon ® Mechanical Turk ® (MTurk). Two screening criteria that will be specified are that only participants that are 18 years of age or older and are currently registered as MTurk workers from the United States will be eligible to take part in the study. The participants will be recruited via a uniform resource locator (URL) link on the MTurk hosting platform. The title of the link will be "Use of Biometric Technology at Airports Survey" and will take participants initially to the Consent Form and then to the survey instrument.
There will be a minimum of 500 participants that will be recruited for the study.

6. Risks or Discomforts: Describe any potential risks to the dignity, rights, health or welfare of the human subjects. All other possible options should be examined to minimize any risks to the participants.

The risks of participating in this study are no more than what is experienced in daily life.

7. Benefits: Assess the potential benefits to be gained by the subjects as well as to society in general as a result of this project.

There are no known benefits to participants from completing the survey. The study is also expected to promote the advancement of knowledge about passengers' intentions to use biometric technologies at airports.

8. Informed Consent: Describe the procedure you will use to obtain informed consent of the subjects. How and where will you obtain consent? See Informed Consent Guidelines for more information on Informed Consent requirements.

The first section of the online survey provides Instructions and a consent form. The consent form includes requirements for participants to confirm that they are at least 18 years of age and to agree to their participation in the study. Participants will also be informed that participation in the study is voluntary and that they could choose to withdraw at any point during the survey with no consequences.

9. Confidentiality of Records: Will participant information be anonymous (not even the researcher can match data with names), confidential (Names or any other identifying demographics can be matched, but only members of the research team will have access to that information. Publication of the data will not include any identifying information.), or public (Names and data will be matched and individuals outside of the research team will have either direct or indirect access. Publication of the data will allow either directly or indirectly, identification of the participants.)?

Anonymous

9b. Justify the classification and describe how privacy will be ensured/protected.

To assure anonymity, the study will not require participants to disclose any personally identifiable characteristics. Only general demographic information will be requested and there is no way to identify any participant from the information that will be provided. Identification numbers will be used to represent participants, while the computer systems used to store data will be password-protected. Any information collected as part of this study will not be used for any future research, and all raw data will be destroyed as soon as the data analysis is concluded.

10. Privacy: Describe the safeguards (including confidentiality safeguards) you will use to minimize risks. **Indicate what will happen to data collected from participants that choose to "opt out" during the research process.** If video/audio recordings are part of the research, describe how long that data will be stored and when it will be destroyed.

All data will remain anonymous throughout the data collection and analysis period. If any participant chooses to withdraw from the study prior to completing the questionnaire, the data collected will be removed and will be destroyed.

11. Economic Considerations: Are participants going to be paid for their participation?

Yes

11b. What will the compensation be?
Describe your policy for dealing with participants who 1) Show up for research, but refuse informed consent; 2) Start but fail to complete research.

It is expected that the compensation amount will not exceed 50 U.S. cents per participant. Participants that complete the survey will be given a verification code number which could be used to receive their reward from the MTurk website. Participants who refuse informed consent will not be able to complete the study. Participants who start but fail to complete the task by leaving answers blank will still be entitled to receive the compensation.

By submitting this application, you are signing that the Principal Investigator and any other investigators certify the following:
1. The information in this application is accurate and complete
2. All procedures performed during this project will be conducted by individuals legally and responsibly entitled to do so
3. I/we will comply with all federal, state, and institutional policies and procedures to protect human subjects in research
4. I/we will assure that the consent process and research procedures as described herein are followed with every participant in the research
5. That any significant systematic deviation from the submitted protocol (for example, a change in the principal investigator, sponsorship, research purposes, participant recruitment procedures, research methodology, risks and benefits, or consent procedures) will be submitted to the IRB for approval prior to its implementation
6. I/we will promptly report any adverse events to the IRB

Electronic Signature:

Kabir Olaseni Kasim

Appendix B

Questionnaire

Section 1: Informed Consent Form

Use of Biometric Technology at Airports Survey

Section 1: CONSENT FORM

PURPOSE OF THIS RESEARCH: You are invited to participate in a research study to evaluate the use of biometric technologies at airports. During this study, you will be asked to complete an online survey about your opinions on various factors that influence passengers' intentions to use biometric technologies at airports. It will take approximately 10 minutes to complete the study.

ELIGIBILITY: To be eligible to take part in this study, you must be 18 years old and above, and your MTurk worker account must be registered in the United States.

RISKS OR DISCOMFORTS: The risks that could result from completing this survey are no more than the normal risks from your everyday activities.

BENEFITS: There are no benefits to you from participating in this study. However, your completion of the study will help promote the advancement of knowledge about passengers' intentions to use biometric technologies at airports.

CONFIDENTIALITY OF RECORDS: All data that will be collected during the study will be anonymous, and there is no way for the researchers to learn your identity. No identifiable personal information will be collected other than basic demographic information, while the online survey system will not save any IP addresses from participants. All information will be kept securely in a password-protected file on a password-protected computer, while all raw data will be destroyed as soon as the data analysis is concluded. Information collected as part of this research will not be used or shared to any other parties for future research studies

COMPENSATION: You will receive compensation that is not expected to be more than 50 cents for taking part in this study.

CONTACT: If you have any questions or would like further information about this research project, you can contact Kabir Kasim at kasimk@my.erau.edu. If you have concerns about the treatment of research participants, you can contact the Institutional Review Board (IRB) Administrator, Teri Gabriel at teri.gabriel@erau.edu or call 386-226-7179.

VOLUNTARY PARTICIPATION: Your participation in the study is completely voluntary and you may choose to decline to participate, without penalty or loss of benefits to which you are otherwise entitled, at any time prior to or during the survey. You may also decline to answer any question in the questionnaire for any reason and this will not be held against you. If you choose to withdraw from the study prior to completing the questionnaire, the data collected will be removed and will be destroyed.

CONSENT: Checking "Yes" below means that you understand the information on this form, that any questions you may have about this study have been answered, and that you are eligible and voluntarily agree to participate in this survey. Checking "No" or closing the browser will end this survey.

Please print a copy of this form for your records. A copy of this form can also be requested from Kabir Kasim at kasimk@my.erau.edu.

○ Yes, I would like to participate. (Please start the survey)

○ No, I do not want to participate. (Please end the survey)

Section 2: INSTRUCTIONS AND ELIGIBILITY QUESTIONS.

This section will present screening questions to confirm your country of registration as an MTurk worker and to confirm that you are above 18 years of age. Answering 'No' to either of the questions will automatically exit the study.

Following this, you will then be asked to complete a series of questions about your opinions towards technology uses at airports before proceeding to answer some demographic questions. When you have completed the survey, you will be required to enter a verification code number which could be used to receive your reward from the MTurk website.

1. Are you currently registered as an MTurk worker in the United States?

○Yes (Please continue the survey) ○No (Please exit the survey)

2. Are you 18 years of age or older?

○Yes (Please continue the survey) ○No (Please exit the survey)

Section 3: FACTORS INFLUENCING PASSENGERS' INTENTIONS TO USE BIOMETRIC TECHNOLOGIES AT AIRPORTS.

INFORMATION FOR SCENARIO AND FOLLOWING STATEMENTS:

Biometric systems involve the use of body characteristics to provide identification. Some of the more common examples in use include fingerprints, signatures, hands, faces, and irises of the eyes. The most common uses of biometric systems at airports include technologies for customs and immigration purposes, security access, accessing itineraries, and for enabling self-check in/self-boarding processes.

For the following statements, please imagine the following scenario:

You have arrived at your local airport for a scheduled flight between two major cities. Upon approaching the check-in area, you are advised that there is an option to complete your entire check-in, baggage drop and aircraft boarding using only facial recognition as the means of identification and verification for the flight.

Please respond to the following statements:

1.

Item Number	Statement	Strongly Disagree (-2)	Disagree (-1)	Neutral (0)	Agree (+1)	Strongly Agree (+2)
AT1	Using biometrics at airports is a good idea	○	○	○	○	○
AT2	Using biometrics at airports is a wise idea	○	○	○	○	○
AT3	I like the idea of using biometrics at airports	○	○	○	○	○
AT4	Using biometrics at airports would be pleasant	○	○	○	○	○

2.

Item Number	Statement	Strongly Disagree (-2)	Disagree (-1)	Neutral (0)	Agree (+1)	Strongly Agree (+2)
SN1	People who influence my behavior would think that I should use biometrics at airports	○	○	○	○	○
SN2	People who are important to me would think that I should use biometrics at airports	○	○	○	○	○
SN3	People whose opinions I value would prefer me to use biometrics at airports	○	○	○	○	○

3.

Item Number	Statement	Strongly Disagree (-2)	Disagree (-1)	Neutral (0)	Agree (+1)	Strongly Agree (+2)
PB1	I would be able to use biometrics at airports	○	○	○	○	○
PB2	The choice to use biometrics at airports is entirely up to me	○	○	○	○	○
PB3	I have the resources and the knowledge and the ability to make use of biometrics at airports	○	○	○	○	○

4.

Item Number	Statement	Strongly Disagree (-2)	Disagree (-1)	Neutral (0)	Agree (+1)	Strongly Agree (+2)
PE1	My interaction with biometrics at airports is clear and understandable	○	○	○	○	○
PE2	Learning to use biometrics at airports is easy for me	○	○	○	○	○

PE3	It would be easy for me to become skillful at using biometrics at airports	○	○	○	○	○
PE4	I would find biometrics at airports easy to use	○	○	○	○	○

5.

Item Number	Statement	Strongly Disagree (-2)	Disagree (-1)	Neutral (0)	Agree (+1)	Strongly Agree (+2)
PU1	Using biometric systems would enable me conduct airport identification and verification processes quickly	○	○	○	○	○
PU2	Using biometric systems would make it easier for me to conduct airport identification and verification processes	○	○	○	○	○
PU3	I would find biometric systems useful in conducting airport identification and verification processes	○	○	○	○	○

6.

Item Number	Statement	Strongly Disagree (-2)	Disagree (-1)	Neutral (0)	Agree (+1)	Strongly Agree (+2)
PR1	I am concerned that when I give personal information to biometric systems for some reason, the owner of the system would use the information for other reasons	○	○	○	○	○
PR2	I am concerned that my information could be breached when using biometric systems	○	○	○	○	○
PR3	I am concerned that my information could be shared or sold when using biometric systems	○	○	○	○	○

7.

Item Number	Statement	Strongly Disagree (-2)	Disagree (-1)	Neutral (0)	Agree (+1)	Strongly Agree (+2)
IN1	Assuming that I have access to biometrics systems at airports, I intend to use them.	○	○	○	○	○
IN2	I intend to increase my use of biometrics at airports in the future	○	○	○	○	○

IN3	Even if there are other options available, I intend to use biometrics at airports	○	○	○	○	○

8.

Item Number	Statement	Strongly Disagree (-2)	Disagree (-1)	Neutral (0)	Agree (+1)	Strongly Agree (+2)
CV1	Thinking about the coronavirus (COVID-19) makes me feel threatened.	○	○	○	○	○
CV2	I am afraid of the coronavirus (COVID-19).	○	○	○	○	○
CV3	I am stressed around other people because I worry I will catch the coronavirus (COVID-19).	○	○	○	○	○

9. Has the coronavirus (COVID-19) crisis affected your perception of intention to use biometrics at airports?

○ No

○ Yes………………………………………………………………………………………..

10. Please state any additional comments you may have on the use of biometrics systems

Section 4: Demographic Information

Please respond to the following questions to provide demographic information.

1. Age: Please state your age in years

2. Gender: Please select your gender

   ○ Male ○ Female ○ Other……………………

3. Education: Please select your highest level of education attained

◯ High school certificate ◯ Bachelor's Degree

◯ Master's Degree ◯ Doctorate Degree

4. Please indicate your ethnicity

◯ American Indian or Alaska Native

◯ Asian or Asian American

◯ Black or African American

◯ Hispanic or Latino

◯ Mixed race

◯ Native Hawaiian or other Pacific Islander

◯ White or Caucasian

◯ Other……………………………………

5. Please indicate your annual total income in USD

6. Have you used facial recognition technology for the purpose of identification and verification at an airport?

◯ No

◯ Yes, once only

◯ Yes, more than once

Section 5: Conclusion

Thank you for completing the survey! You are done now. **Please input your initials followed by your age. For example, if your name is John Smith and you are 23 years old, then you would put: JS23**

Please return to MTurk and enter this code into the appropriate place so that you can be paid for your time.

Appendix C

Variables Definitions and Items Used

Construct/ Variable	Operational Definition/Description	Items Used	Adapted from
Attitudes	A passenger's positive or negative feelings about using biometrics	AT1: Using biometrics at airports is a good idea AT2: Using biometrics at airports is a wise idea AT3: I like the idea of using biometrics at airports AT4: Using biometrics at airports would be pleasant	Chen, Fan, and Farn (2007), Taylor and Todd (1995)
Subjective Norms	A passenger's perception that most people important to the passenger think he should or should not use biometrics	SN1: People who influence my behavior would think that I should use biometrics at airports SN2: People who are important to me would think that I should use biometrics at airports SN3: People whose opinions I value would prefer me to use biometrics at airports	Chen, Fan, and Farn (2007), Reza Jalilvand and Samiei (2012), Taylor and Todd (1995)
Perceived Behavioral Control	A passenger's perception of the control regarding the decision to use biometrics	PB1: I would be able to use biometrics at airports PB2: Using biometrics at airports is entirely within my control. PB3: I have the resources and the knowledge and the ability to make use of biometrics at airports	Taylor and Todd (1995)
Perceived Ease of Use	The degree to which a passenger believes that using biometrics would be free of effort	PE1: My interaction with biometrics at airports is clear and understandable PE2: Learning to use biometrics at airports is easy for me PE3: It would be easy for me to become skilful at using biometrics at airports PE4: I would find biometrics at airports easy to use	Lu, Chou, and Ling (2009), Wang, Wang, Lin, and Tang (2003)

Perceived Usefulness	The degree to which a passenger believes that using biometrics would be advantageous for them	PU1: Using biometric systems would enable me conduct airport identification and verification processes quickly PU2: Using biometric systems would make it easier for me to conduct airport identification and verification processes PU3: I would find biometric systems useful in conducting airport identification and verification processes	Lu, Chou, and Ling (2009), Wang, Wang, Lin, and Tang (2003)
Coronavirus (COVID19)	A passenger's perception of the threat of the impact of the coronavirus (COVID-19) crisis on the use of biometrics	CV1: Thinking about the coronavirus (COVID-19) makes me feel threatened. CV2: I am afraid of the coronavirus (COVID-19). CV3: I am stressed around other people because I worry I will catch the coronavirus (COVID-19).	Conway, Woodard, and Zubrod (2020)
Privacy concerns	A passenger's perception of the collection, use, and management of the passenger's personal information while using biometrics	PR1: I am concerned that when I give personal information to biometric systems for some reason, the owner of the system would use the information for other reasons PR2: I am concerned that my information could be breached when using biometric systems PR3: I am concerned that my information could be shared or sold when using biometric systems	Albashrawi and Motiwalla (2017), Hong and Thong (2013)
Intention to Use	A passenger's intentions to use biometrics	IN1: Assuming that I have access to biometrics systems at airports, I intend to use them IN2: I intend to increase my use of biometrics at airports in the future IN3: Even if there are other options available, I intend to use biometrics at airports	Al Ziadat (2015); Lu, Chou, and Ling (2009), Wang et al. (2003)